INTELLIGENT OPTIMAL CONTROL OF THERMAL VISION-BASED PERSON-FOLLOWING ROBOT PLATFORM

by

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In this paper the supervisory control of the Person-Following Robot Platform is presented. The main part of the high level control loop of mobile robot platform is a real-time robust algorithm for human detection and tracking. The main goal was to enable mobile robot platform to recognize the person in indoor environment, and to localize it with accuracy high enough to allow adequate human-robot interaction. The developed computationally intelligent control algorithm enables robust and reliable human tracking by mobile robot platform. The core of the recognition methods proposed is genetic optimization of threshold segmentation and classification of detected regions of interests in every frame acquired by thermal vision camera. The support vector machine classifier determines whether the segmented object is human or not based on features extracted from the processed thermal image independently from current light conditions and in situations where no skin color is visible. Variation in temperature across same objects, air flow with different temperature gradients, person overlap while crossing each other and reflections, put challenges in thermal imaging and will have to be handled intelligently in order to obtain the efficient performance from motion tracking system.

Key words: *computational intelligence, genetic optimization, thermal vision*

Introduction

The relevance of technology in our lives has grown significantly in the last decades. Intelligent service robots, a research field that became more and more popular over the last years, cover a wide range of application scenarios, from robotic assistance for disabled or elderly people up to climbing machines for cleaning large storefronts. In the next few years, personal service robots are expected to become part of our everyday life, playing an important role as our appliances, servants, and assistants. The future of smart homes points clearly towards the ambient intelligence paradigm. We expect to build an intelligent environment that discovers and adapts itself automatically to the user's needs. In this environment, service robots are completely integrated in the home and it is easy to imagine scenarios in which robots and smart home systems cooperate. Unfortunately, the road toward ambient intelligence is full of obstacles [1, 2].

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As research robots move closer towards real applications in populated environments, these systems will require robust algorithms for tracking people to ensure safe human-robot cohabitation. These robots will need to be able to track human motion to avoid colliding with them, to acquire a sufficient understanding of the environment, to be aware of different situations, to detect and track people with minimum instruction and with high quality and precision, and also to be able to make decisions based on their perception of human state in order to become functional collaborators [1-3].

The multiple people tracking problem is well-known in computer vision, where there are developed systems used mostly in surveillance, identity verification and automatic motion capturing and human motion analysis with one or more static cameras. In these environments, moving objects can be easily detected using background subtraction techniques [4, 5].

In the case of mobile robots, these tasks become more challenging since the robot is moving and the environment is unpredictable so that background subtraction methods cannot be applied. Developed robot vision systems should be robust due to increased noise and moving background and it also needs to be fast so the robot can work in real-time and non-invasive so the normal human activity can be unaffected [6].

Existing people recognition systems on mobile robots use information from range sensors such as laser scanners and ultrasonic sensors or a color camera as the primary sensor [1, 2, 4-6]. Thermal vision helps to overcome some of the problems related to color vision sensors, there are no major differences in appearance between different persons in a thermal image and sensor data does not depend on light conditions.

There are many algorithms focusing specifically on the thermal domain for human tracking in robotics. The thermal-based algorithms are inspired in the biological processes of many animals and insects, which are affected by the presence of thermal energy in their environment. Indeed, diverse types of thermoreceptors are found in nature, which aid animals and insects in hunting, feeding, and survival. Now, in computer vision, the unifying assumption in most methods is the belief that the objects of interest are warmer than their surroundings. Indeed, some animals can see in total darkness, or even see colors beyond the visual spectrum, that humans have never seen. Thermal infrared video cameras detect relative differences in the amount of thermal energy emitted/reflected from objects in the scene. As long as the thermal properties of a foreground object are slightly different (higher or lower) from the background radiation, the corresponding region in a thermal image appears at a contrast from the environment [7].

In order to determine the position of human in acquired thermal image that will enable robot supervisory control, it is necessary to do the appropriate segmentation of the thermal image. The idea presented in many papers considering segmentation in robot vision and particularly thermal vision is to determine threshold [8-10] in order to get region of interest (ROI). However, it is not always enough to determine single threshold state for entire sequence/acquired image in both color and thermal images. There have been many successful attempts of developing intelligent systems for image segmentation using multilevel thresholding and adaptive thresholding based on neural network and/or fuzzy inference system [9-12]. Although developed algorithms for advanced thermal image segmentation give more than satisfactory results, they are only adequate for offline applications. For robotic application when calculations need to be done in real time these algorithms must be improved, optimized and if necessary simplified with uncompromised accuracy and robustness.

The system we have developed to solve the person-following task uses computational intelligence for solving different problems of robot vision [13]. The robot will use information provided by a thermal camera to detect human and to track him. The information about position of the person in the scenario will then be sent to a motion controller that controls motors of the mobile robot platform in order to follow target. The thermal vision system will detect the presence of people around the robot by using human detection and tracking algorithm developed in this paper. The developed algorithm has two main parts, image segmentation part and classification part. Previous research of the authors [3, 6, 8] has shown that full potential of intelligent methodologies used for classification of ROI in robot vision can be achieved only if reliable and robust segmentation is done. Variation in temperature across the same objects, air flow with different temperature gradients, person overlap while crossing each other and reflections, put challenges in thermal imaging segmentation. Therefore these problems need to be handled intelligently in order to obtain the efficient performance from motion tracking system. In order to improve fuzzy segmentation algorithm with manually determined threshold [3], in this paper authors are suggesting implementation of genetic optimization for offline threshold determination. After segmentation is done support vector machine classifier determines whether segmented ROI is human or not based on features extracted from binary segmented image and center of mass is calculated. This vision module will provide the angle at which the human is located with respect to the forward direction of the robot so that robot platform can undisturbedly track a person.

Experimental set-up

For development of reliable mobile robot platform that is capable of tracking people based on thermal image National Instruments Robotics Starter Kit 1.0 known as DaNI robot has been combined with FLIR E50 thermal camera. Thermal camera could not be directly connected to On-Board Controller (Single Board RIO) of DaNI Robot, nor could the complex segmentation and classification algorithms be implemented directly to low level control algorithm, so additional Off-Board personal computer was used for thermal vision image processing and high level control. Functional scheme of the thermal vision-based person-following robot platform is shown in fig. 1.

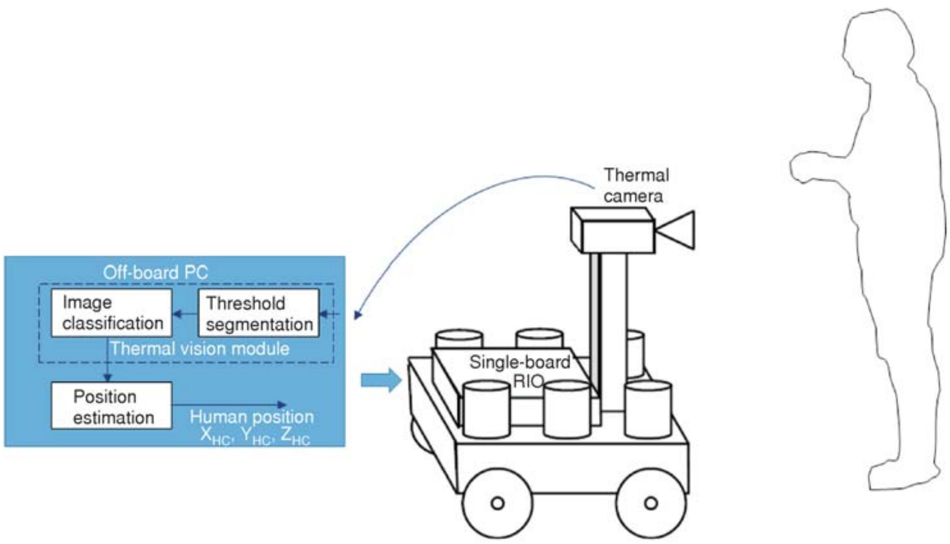

Figure 1. Principle layout of thermal vision-based person-following robot platform

Acquired thermal image is segmented and segmented objects are then classified in thermal vision module in order to detect human. Segmentation and classification algorithms are two main parts of Thermal vision module, a part of High level control system of mobile robot platform. After person was detected, simple estimation algorithm that uses average human height as a reference estimates relative position for the following task. Co-ordinates are then sent to low level controller that uses conventional PID controllers for wheel velocities.

DaNI robot

NI Robotics Starter Kit 1.0, known as DaNI robot (fig. 2) is a mobile robot platform that features sensors, motors, and NI Single-Board RIO hardware for embedded control [3, 6]. DaNI is a four-wheel robot, powered with two motors and equipped with ultrasonic distance sensor for distance measurements.

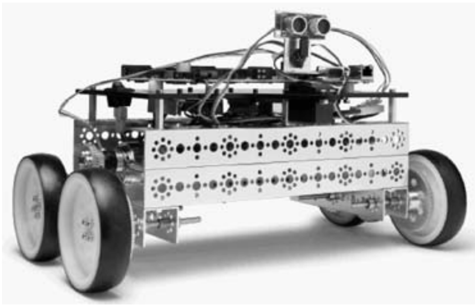

Figure 2. DaNI mobile robot platform

The NI sbRIO-9632 embedded control and acquisition device integrates a real-time processor, a user-reconfigurable field-programmable gate array (FPGA), and I/O on a single printed circuit board (PCB). It features a 400 MHz industrial processor, a 2M gate Xilinx Spartan FPGA, 110 3.3 V (5 V tolerant/TTL compatible) digital I/O lines, 32 single-ended/16 differential 16-bit analogue input channels at 250 kS/s, and four 16-bit analogue output channels at 100 kS/s.

It also has three connectors for expansion I/O using board-level NI C Series I/O modules. The sbRIO-9632 offers a –20 to 55 °C operating temperature range, and includes a 19 to 30 VDC power supply input range, 128 MB of DRAM for embedded operation, and 256 MB of non-volatile memory for storing programs and data logging.

The mobile robot platform has a built-in 10/100 Mbit/s Ethernet port that can be used to conduct programmatic communication over the network and host built-in Web (HTTP) and file (FTP) servers. The programming of the sbRIO-9632 device is done by the LabView graphical development environment. The real-time processor runs the LabView Real-Time Module on the Wind River VxWorks real-time operating system (RTOS) for extreme reliability and determinism. LabVIEW contains built-in drivers and API for handling data transfer between the FPGA and real-time processor.

Thermal image information

Thermographic cameras detect radiation in the infrared range of the electromagnetic spectrum (roughly 9-14 μm) and produce images of that radiation, called thermograms. Since infrared radiation is emitted by all objects above absolute zero according to the black body radiation law, thermography makes it possible to see one's environment with or without visible illumination. The amount of radiation emitted by an object increases with temperature; therefore, thermography allows one to see variations in temperature. When viewed through a thermal imaging camera, warm objects stand out well against cooler backgrounds [14]; humans and other warm-blooded animals become easily visible against the environment, day or night.

The experimental mobile robot platform was equipped with an array of sensors including a thermal camera FLIR E50 shown in fig. 3(a). The camera can detect infrared radiation and convert this information into an image where each pixel corresponds to a temperature value [3] (see fig. 3(b).

The resolution of the thermal camera is 240 × 180 pixels, so total number of the pixels is 43,200. The thermal sensitivity of the camera is less than 0.05 °C and the accuracy is ±2 °C or ±2% of reading within the temperature range from –20°C to 650 °C. The frame rate is 60 Hz and operating times 4 hours. The weight of thermal camera is 0.825 kg and that is not neglectable but it does not significantly affect the mobile robot platform dynamics.

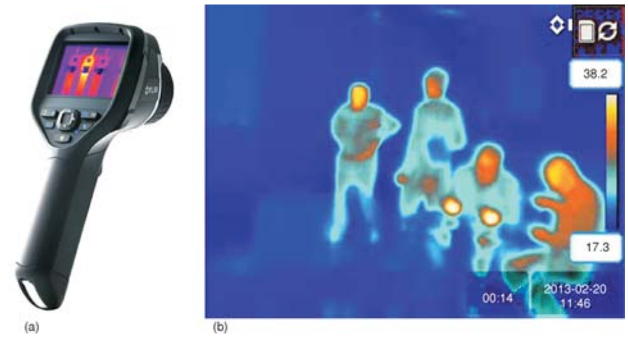

Figure 3. FLIR E50 thermal camera (a) and thermal image (b)

The robot was operated in an unconstrained indoor environment (a corridor and a hallway at our Faculty). Persons taking part in the experiments were asked to walk in front of the robot while it performed two different autonomous patrolling behaviors: corridor following (based on sonar readings) and person following (using information from the implemented tracker), or while the robot was stationary. In our experiments the visible range on the image was equivalent to the temperature range from 17.3 to 38.2 °C and one of predefined six color palettes has been chosen.

People detection and tracking system

Most vision-based people recognition systems concern non-mobile applications *e. g.*, surveillance or identity verification systems, where detection of persons can be solved easily by background subtraction methods that cannot be applied to mobile systems. Existing vision-based people recognition systems on mobile robots typically use skin color and face detection algorithms. However these approaches assume the frontal pose of a person and require that the person is not too far from the robot. Thermal vision helps to overcome some of the problems related to color vision sensors since humans have a distinctive thermal profile compared to non-living objects.

To track a person in the thermal image we use advanced threshold determination that uses genetic algorithm and a priori knowledge for image segmentation and support vector machine for image classification. The thermal camera can detect infrared radiation and convert this information into an image where each pixel corresponds to a temperature value, and in greyscale image darker shades correspond to lower temperature and brighter pixels corresponds to higher temperature.

Optimal threshold determination

Four indoor videos were made in different real world scenarios, all made under diverse lighting where there are obstacles in front of the person, two persons are overlapping when moving close to one another and reflection is possible to occur. First idea was to make classifier based on features of manually segmented images. However, in a real world application segmentation algorithm will not be as good and accurate and we needed to implement solution closer to real world problem [3]. Therefore we have explored the idea of determining one set of threshold parameters that is applicable for every scenario.

Based on 50 randomly selected and manually segmented images from every captured thermal video, genetic algorithm optimization is used to determine optimal value of threshold parameters. The problem boils down to multi-objective optimization of two parameters, namely upper T_{high} and lower T_{low} threshold bounds, involving 200 objective functions to be optimized simultaneously. The goal functions are as follows:

$$g_i(T_{\mathrm{low}}, T_{\mathrm{high}}) = \left\| \vec{\mathrm{y}}(T_{\mathrm{low}}, T_{\mathrm{high}}) - \vec{\hat{\mathrm{y}}}_i \right\| \tag{1}$$

where *i* takes values from 1 to 200, vectors $\vec{\mathrm{y}}_{\mathrm{i}}$ and $\vec{\hat{\mathrm{y}}}_{\mathrm{i}}$ are of size 4320 and made of rows of matrices $[\mathbf{A}]$ and $[\hat{\mathbf{A}}]$, respectfully.

Matrix $[\mathbf{A}]$ is 240 × 180 matrix that represents segmented image, value of each matrix element can be 0 or 1 and it depends on upper T_{high} and lower T_{low} threshold bounds. Matrix $[\hat{\mathbf{A}}]$ is 240 × 180 binary image matrix that represents manually segmented image. Thermal image, manually segmented image, and threshold segmented image are shown in fig. 4.

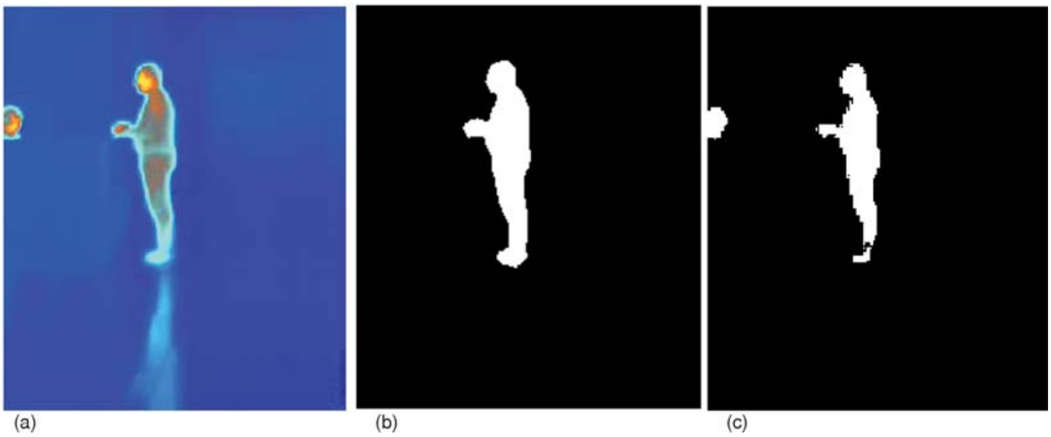

Figure 4. Thermal image (a), manually segmented image (b), and threshold segmented image (c)

Since the problem of segmentation of thermal image needs involving some intelligent and heuristic optimization algorithm the authors have decided to test genetic algorithm (GA) for this purpose. GA maintains and manipulates a population of solutions and implements a survival of the fittest strategy in their search for better solutions. The fittest individuals of any population tend to reproduce and survive to the next generation thus improving successive generations. The inferior individuals can also survive and reproduce. Implementation of genetic algorithm requires the determination of six fundamental issues: chromosome representation, selection function, the genetic operators, initialization, termination, and evaluation function [15].

The fitness function is designed by scalarizing a multi-objective optimization problem with very well-known linear scalarization method:

$$\min_{T_{\mathrm{low}}, T_{\mathrm{high}}} \sum_{i=1}^{200} w_i g_i(T_{\mathrm{low}}, T_{\mathrm{high}}) \tag{2}$$

where the weights of the objectives $w_i > 0$ are the parameters of the scalarization, and in our case $w_i = 1$, since every frame of every video is of equal significance.

In the implemented algorithm a population of 30 individuals, an elitism of 3 individuals was used, initial population was randomly generated and initial range was 0.255. A scattered crossover function was performed, that creates a random binary vector and then selects the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child. All the members are subjected to mutation except the elite. The mutation operator is adaptive feasible. As the result of the offline genetic parameter tuning, optimal upper T_{high} and lower T_{low} threshold bounds were determined.

Feature extraction

After segmentation is successfully done in some cases (frames) not only humans are segmented but also reflections and other objects with approximate temperature or some disturbances can occur. In order to detect position of humans it is necessary to determine if segmented object is a person. For such a task the input parameters of the classifier must be some shape descriptors, like proportionality, connectivity, Hu set of invariant moments or some other feature [8].

As the inputs of designed classifier, after series of trials and testing, 4 shape descriptors were selected, namely proportionality P and first three Hu invariant moments, I_1, I_2, and I_3. The proportionality of a region of connected segmented pixels:

$$P = \frac{h}{w} \tag{3}$$

is ratio between height h and width w of the bounding box of the segmented region. The bounding box is the smallest rectangle containing the segmented region.

Hu moments are invariant coefficients which are derived from moments of the image region [16]. In case of digital image intensity function $f(x, y)$, the moment of order $(p+q)$ is:

$$m_{\mathrm{pg}} = \sum_x \sum_y x^p y^g f(x, y) \tag{4}$$

where x and y are pixel co-ordinates in the considered image region. The central moments m_{pq} are defined as:

$$\mu_{\mathrm{pg}} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x, y) \tag{5}$$

where p and g = 1, 2, 3, ... , $\bar{x} = \mathrm{m}_{10}/\mathrm{m}_{00}$, $\bar{y} = \mathrm{m}_{01}/\mathrm{m}_{00}$. In case of a binary image:

$$f(x, y) = \begin{cases} 1, \text{ if } & f(x, y) \in C \\ 0, \text{ if } & f(x, y) \notin C \end{cases} \tag{6}$$

and C is a subinterval of upper and lower thresholds $C \in [T_{\mathrm{low}}, T_{\mathrm{high}}]$.

In the presented system for object classification first three Hu moments were used:

$$I_1 = \eta_{02} + \eta_{20} \tag{7}$$

$$I_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{8}$$

$$I_3 = (\eta_{30} - \eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{9}$$

where η_{pg} is the normalized central moment:

$$\eta_{\mathrm{pg}} = \mu_{\mathrm{pg}} \mu_{00}^{-1-\frac{p+g}{2}} \tag{10}$$

Classification

The recognition of human, using computationally intelligent classifier was done based on the proportionality descriptor and first three Hu invariant moments extracted from the resulting binary segmented images. For real world application it is of particular interest to perform object classification reliably and effectively. This means that the applied classifier has to satisfy goals of high recognition accuracy and small computing time.

In machine learning, support vector machines (SVM) are supervised learning models with associated learning algorithms that analyzes data and recognizes patterns, used for classification and regression analysis. Their remarkably robust performance with respect to sparse and noisy data is making them the system of choice in a number of applications [17, 18].

When used for classification, they separate a given set of binary labelled training data with a hyper-plane that is maximally distant them. For cases in which no linear separation is possible, they can work in combination with technique of 'kernels', that automatically realizes a non-linear mapping to a feature space. The hyper-plane found by the SVM in the feature space corresponds to a nonlinear decision boundary in the input space.

The complete SVM method can be described as follows [19, 20]: we begin by choosing a kernel, starting with a simple dot-product kernel, and tune the diagonal factor to achieve the best performance on hold-one-out cross-validation test using the full dataset. The SVM tuning procedure is then repeated with a specified number of the top-ranked features. Two hundred frames randomly selected from four different videos taken with different people and in different scenarios were segmented and then divided into images with different manually labelled objects. Dataset of 512 objects with four features each was used for training, validation and testing of the support vector machine classifier. In the SVM classifier training shown in this paper, only simple dot-product kernel is used and more complex kernel was not required. However, for more complex dataset, higher-order kernels can be applied.

Evaluation

The problem of evaluating tracking systems has been addressed recently by the computer vision community [7]. The consensus is that there is no single metric that could indicate sufficiently the quality of the entire system. For a proper evaluation it is important to use different metrics quantifying different performance aspects of the system. Having a good set of performance measures allows to optimize algorithm parameters, check performance of the tracker for different kinds of data, quantitatively compare different algorithms, support development of the algorithm, and decide upon trade-offs between different performance aspects. The evaluation procedure requires that ground truth information is available. In the case of video data this is often a difficult, monotonous, and labor demanding process. There were attempts to improve and automate this process by using some other algorithm to roughly select regions of interest that are refined later by hand, synthesized ground truth data, or systems performing fully automatic evaluation based on color and motion metrics.

The obtained classification results are very good, as indicated by the fact that the classification performance rate was above 97.3%. Mis-classification happened only in cases of significant object occlusion, which resulted in the improper value of feature measure of a segmented object region. To analyze the performance of the recognition and following of human we used results received from a mobile robot platform and LabVIEW (fig. 5). People detected in thermal image are inside the yellow bounding boxes, and all the objects that are segmented and not human are neglected.

The objects captured by thermal camera installed on mobile robot platform with similar temperature as people were for instance hot tea and coffee cups and different heating sources like air condition devices. A major difficulty for all tracking systems involving multi-target tracking is the problem of occlusions. The tracker is able to detect and track multiple persons but the performance of the tracking system depends on crossings and occlusions.

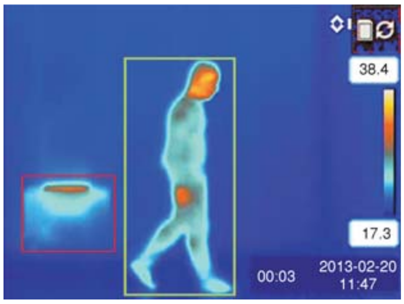

Figure 5. Person detected in thermal image by mobile robot platform

Conclusions

This paper presented a people tracking system for mobile robots using thermal vision. The system uses a robust and fast tracking method based on threshold segmentation and support vector machine classifier. For the optimal threshold determination genetic optimization was used. Based on features extracted from the processed thermal image classifier determines whether the segmented object is human or not. The results indicate good detection performance and consistent tracking in the case of single persons independently from current light conditions and in situations where no skin color is visible. The tracker is also able to detect and track multiple persons. The performance of the tracking system here depends heavily on the intensity of interaction between persons. The tracker tends to easily lose the track in such cases but it recovers quickly from tracking failures. Future work would include incorporating adaptive segmentation algorithm and action recognition as well as other sensors in thermal vision-based mobile robot platform.

Experimental results show that this kind of approach in robot vision for human detection and tracking gives good results. Using the fact that suggested intelligent segmentation algorithm and SVM classifier can handle different indoor scenarios, and on the other hand classifier made decisions which are reliable and accurate, algorithm used in paper can be implemented in different tasks for mobile robot platform with thermal vision.

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