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# A Review of Infrared Spectrum in Human Detection for Surveillance Systems

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**Abstract**—Human detection of the infrared spectrum of the image is a very relevant area of research that potentially impacts the design of surveillance systems. There are many suggestions in the literature, but they do not have a comparative. Therefore, first and foremost in this paper we propose a common framework in which we have adapted it with a different approach, and secondly, we use this framework to provide a comparative point of view that can lead to what the details of different approaches, it is also the main challenges to be solved in the future. In summary, we expect this review useful for new and experienced researchers in this field. The first aim, as a describe overview state of the art, and second, as a way to introduce the trend and draw from this comparative study.

**Index Terms—**Infrared spectrum, human detection, surveillance, roi generation, object classification

## 1 INTRODUCTION

THE issue of security surveillance is a global problem, in which most country willing to spend lot of money to get an security surveillance systems advanced and effective. Security issues are usually referred to the institutions such as military (national defence), police (public safety) and private security (safety property) in which these institutions are usually use human as manpower. Safety surveillance is very focused at the nighttime because more than 90 percent of cases invasion occurred at nighttime. Moreover, humans have a limited of vision and movement at night. As mentioned in [1], "Humans have poor night vision compared to many animals, in part because the human eye lacks a tapetum lucidum. Night vision is the ability to see in low light conditions. Whether by biological or technological means, night vision is made possible by a combination of two approaches: sufficient spectral range, and sufficient intensity range".

Generally in humans (trespassers) detection, as mentioned in [2], the temperature of people is higher than the environment temperature and their heat radiation is sufficiently high compared to the background. Therefore, in infrared spectrum, images human belong to the upper range in the gray-level scale and are sufficiently contrasted with respect to the surroundings. As such the, we restrict the discussion presented in this paper to works based on image of the infrared spectrum. This problem has led to a sense of lively interest of researchers to develop more effective proposals. However, the most of the works they produce are not made comparisons with the work of others. Therefore, review the comparison is very relevant for new and experienced researchers in this field. In this paper, a survey of works with images of the Infrared spectrum is presented.

The paper is organized as follow. Section II discusses the fundamental of infrared spectrum. A common proposal model architecture are presented in Section III, in which we review the different proposal in the literature. Discussion of the most important topics for future research is present in Section IV. Finally, in Section V, we summarize the conclusions of this paper.

## 2 INFRARED SPECTRUM

Image in the infrared spectrum convey a type of information that is very different from images in the visible spectrum. Basically, in the visible spectrum, the image of the object depends on the amount of incident light on its surface and on how well the surface reflects it. On the other hand, in the infrared spectrum, the image of an object relates to its temperature and the amount of heat it emits.

In Table 1, Infrared is usually divided into 3 spectral regions: near, mid and far-infrared. The boundaries between the near, mid and far-infrared regions are not agreed upon and can vary. The main factor that determines which wavelengths are included in each of these three infrared regions is the type of detector technology used for gathering infrared light. All objects emit infrared radiation. The intensity of the emitted radiation depends on two factors, the temperature of the object and the ability to radiate.

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TABLE 1. INFRARED SPECTRUM REGIONS

| Spectral Region | Range (μm) | Temperature Range (Degrees Kelvin) | Application |
|---|---|---|---|
| NIR | 0.7 - 5 | 740 - 5,200) | Telecommunication, Remote Sensing, High Temperature inspection (indoors scientific research) |
| MIR | 5 - ~30 | ~120 - 740 | Ambient Temperature (outdoor, industrial inspection) |
| FIR | ~30 - ~200 | ~10 - ~120 | Spectrometry, Astronomy (emission from cold dust, central regions of galaxies, very cold molecular clouds) |

## 3 MODEL ARCHITECTURE AND REVIEW

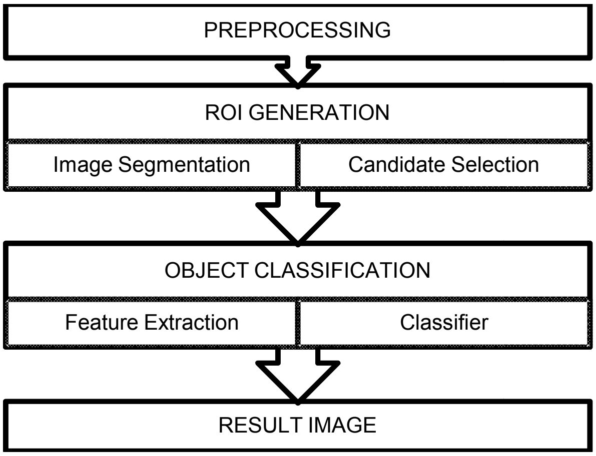


Fig. 1. Model architecture is used as the common framework for the review of the literature.

### 3.1 ROI Generation Stages

First of all, some researchers define ROI as the rough contour or initial contour of the interest object, while the other defines ROI as a rectangular region containing both the interest object and some background information. As in [3], the ROI generation is the first and importantstep since it provides candidate for the following processes and directly affects the system performance. Fortunately, the ROI generation stage can be facilitated by special hardware configuration. While Gavrila et al. 2004 [4], stating that the ROI generation is accepted if its depth distribution agrees with the expected and A. Broggi et al. 2000 [5] also stated the ROI generation is considered as containing a human (trespassers) if there is a good matching with a head-shoulders like binary pattern.

ROI generation requires two steps: Image Segmentation and Candidate Selection. The image segmentation steps adopt two thresholds for each pixel that are calculated from the horizontal scan line to determine the foreground based on the fact that human appear brighter than the nearby background in infrared (IR) image. In [6], intensity of the infrared image is influenced by surface properties and orientation of objects. Therefore, the temperature of the object is the most significant factor among them. Moreover, the human body temperature is stable, where the image intensity differences among human body parts is far less than those between humans and the environment. Instead, as mentioned in [7], ferroelectric thermal sensors typically also have some technical challenges, including low ratio of signal-to-noise (SNR), white/black and hot/cold polarity changes, and halos that appear around very hot or cold objects. Therefore, robust feature extraction from thermal images for human detection is critically essential to ensure that a high performance could be achieved.

The candidate selection step to the connected region that satisfies the scene-related size and position constraints are selected as ROI for the subsequent classification module. This is mentioned in [8], Candidate selection has four constraints: the size and position of objects in the image coordinates, object width/high ratio and constraints convenient form. These constraints can be used to design simple filters to reject candidates for non-human, to keep the calculation and reducing the false recognition rate of the system. There are three advantages in the candidate selection step:

1. Reduce the number of candidates will be sent to the next object classification module can help improve system performance.
2. Reduce the value of FPR by rejecting / remove much of the candidates in advance.
3. Detection rate and durability of the system can be improved by means of producing an additional candidate.

### 3.2 Object Classification

The object classification stage is a key component in human recognition. There are two important points in the classification namely to an accuracy and high efficiency for the practical real-time application. In Object Classification stages, it also has two stages: Feature Extraction and Classifier.

The feature extraction step is a step of selecting strong features of the object to be used as reference, such as image intensity, binary image, gradients magnitude, Haar-like, histogram of oriented gradient (HOG), the co-occurrence matrix, Shapelet and combine [9]. Basically, feature extractions are distinctive elements or geometric primitives of the environment. They usually can be extracted from measurement and mathematically described. The application must be able to determine its relationship to the environment by sensing and interpreting the measured signal. The main difficulty lies in interpreting these data, that is, in deciding what the sensor signals tell us about the environment.

The famous feature in human detection is the HOG feature, where in [8] present a human detection algorithm with excellent detection results by using a single window approach with a dense HOG object representation scheme. Unfortunately, the computational time of their system was approximately 7 seconds, performed by processing a 320×240-pixel image using a dense scanning methodology.

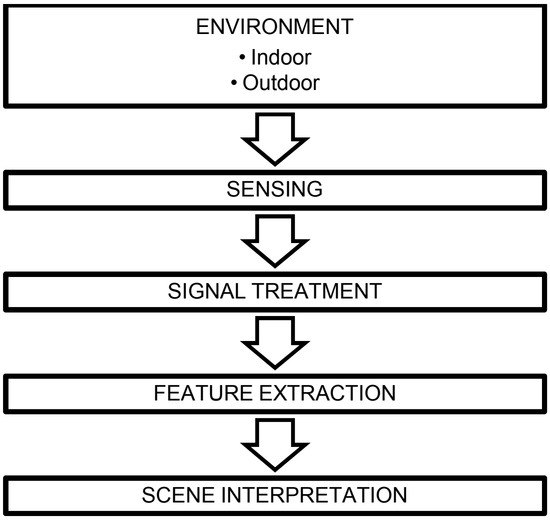


Fig. 2. Scene Interpretation of Feature Extraction

TABLE 2. SURVEILLANCE OF ROBOTIC

| **Identification** | | **ROI Generation** | | **Object Classification** | | | **Performance** | |
|---|---|---|---|---|---|---|---|---|
| **Authors** | **Type of Sensor** | **Segmentation** | **Candidate Selection** | **Feature Extraction** | **Technique and Classification** | **Tracking Method** | **Classifier Performance** | **System Performance** |
| Mauricio et al. 2012, [18] | Dynamic Fusion CVC and TVC | Dynamically updated Skindiff algorithm Mixture of Gaussians | Integrated blob and detection analysis (Heuristics) | Histogram | Nested cascade of boosted | | Average recognizes correctly 3.3 of 4 detection people | Thermal system DR (face) 88.9% (People) 86.6% |
| A. Fernandez-Caballero et al. 2010, [19] | TVC with Mobile platform | Human Blob: Static or dynamic situation | Human Candidate Blob Detection | Warmer body | (*use but not detailed*) | Blob detection, Image subtraction, Optical flow | | Max. DR: (static) 99.5% Precision (dynamic) 97% Precision |
| E. Thomas Gilmore et al 2009, [20] | Dynamic Fusion CVC and TVC | - Threshold - Morphological | Metrics with aspect ratio constraint | Shape and heat flow | SVM | | CR : 87% | DR : (Infusion – TIR) 89% (Fusion) 97% |
| A. Treptow et al. 2006, [21] | TVC with Mobile platform | Not use | Elliptic model | Warmer + Contour + Gray level image | Integral image feature | With Particle filter: Contour model, Feature model, Combination of both model | n/a | (Accuracy)single person: all model 90% plus Multiple person: Contour 85% Feature 80% Combined 83% |
| G. Cielniak et al. 2004, [17] | Dynamic TVC | - Threshold - Noise filtering | Person segmental | Temperature and heu-saturation value (HSV) | Bayes | | CR : 99.7% | DR : 94.04% |
| J.R Martinez et al. 2004, [22] | Dynamic TVC | - Threshold selection | | Histogram | Fuzzy supervising system with ANFIS | | CR : >80% | DR : >90% |

TABLE 3.SURVEILLANCE OF PUBLIC AREA

| **Identification** | | **ROI Generation** | | **Object Classification** | | | **Performance** | |
|---|---|---|---|---|---|---|---|---|
| **Authors** | **Type of Sensor** | **Segmentation** | **Candidate Selection** | **Feature Extraction** | **Technique and Classification** | **Tracking Method** | **Classifier Performance** | **System Performance** |
| Y. Zhang et al. 2011, [23] | Static TVC | MAP-MRF decision framework with Foreground and background subtraction | | Hotspot | AdaBoost | | *CR : 90%* | DR : 98% |
| W.K. Wong et al. 2010, [24] | Static TVC | Binary image conversion, Background filtering and noise filtering | Height and width ratio, and boundary extraction | Heat detection with shape | Use but not detail | | Short routine time : 112ms | DR : 98.62% |
| W. Wang et al. 2010, [25] | Static TVC | Sobel filter | | Shape Context Descriptor | AdaBoost cascade | | *CR: 99.5%* | Average DR: 80% |
| Y. Benezeth et al. 2008, [26] | Static TVC(FIR) | Foreground segmentation with background subtraction (single Gausssion) | Connected component analysis and filtering | Haar-wavelets | AdaBoost cascade of boosted | Neighborhood Blob | | Precision 95.34% Recall 94.78% |
| James et al 2005, [27] | Static TVC | Contour Saliency MAP with sobel derivative masks, and Template | Multi-resolution screening with bounding windows | Gradient operators | Adaboost with adaptive filter | | CR : 100% | DR : 95% |

TVC=Thermal Vision Camera, CVC=Colour Vision Camera

TABLE 4. SURVEILLANCE OF PEDESTRIANS

| Identification | | ROI Generation | | Object Classification | | | Performance | |
|---|---|---|---|---|---|---|---|---|
| Authors | Type of Sensor | Segmentation | Candidate Selection | Feature Extraction | Technique and Classification | Tracking Method | Classifier Performance | System Performance |
| L. Yu-Chun et al. 2011, [28] | Mono TVC (NIR) | Smart region detection (SRD), Intensity, and Haar-like detection | | HOG and Contour extraction; combine | AdaBoots + SVM | n/a | n/a | (Precision) Overall; HOG 97% Contour 100% Combined 98% SRD; HOG 93% Contour 95% Combined 95% |
| J. Ge et al. 2009, [29] | Mono TVC (NIR) | Dual threshold | | Gray level image | AdaBoots with HOG + Haar-like feature | Kalman filter + Template matching | Speed (second): 9.5ms > 90% DR, 2% FPR | Computation cost 29.1ms 93% DR |
| M. Bertozzi et al. 2007, [2] | Stereo TVC (FIR) | Warm area, edge and disparity computation | Warm and vertical edges | Warmer + Vertical edges + Disparity Space image + size | Bounding box: Stereo match, filtering with size & aspect ratio, head search | Sobel + Adaptive threshold + Morphological expansion | | 83% DR and min. FPR |
| T.-J Yun et al 2007, [6] | Mono TVC (FIR) | Histogram cluster analysis using K-mean clustering | Rectangle bounding box | Histogram of maximal energy map using Log-Gabor wavelets | Radial basis function based SVM | | Feature Extraction Accuracy : 100% | DR : 97% |
| F. Xu et al. 2005, [30] | Mono TVC (FIR) | Hotspots detection with road information | | Hotspots or whole body | SVM with gray scale or binary images of hotspots or whole body | Kalman + Mean shift : Heads or Bodies | Speed (second): SVM 40s Motion-based method 5s | 92% DR<br>93% DR |
| Mahlisch et al. 2005, [31] | Mono TVC (FIR) | PSC + Hypermutation Network | | Fusion of Chamfer Contour Matching | Haar Wavelet with cascade | Particle filter for state estimation | CR : 80% | DR : >90% |
| M. Bertozzi et al. 2004, [32] | Mono TVC (FIR) | Focus of attention (interesting regions and vertical edge) | Gray-level & Edge symmetry, and Edge density | Shape + Thermal Characteristics | Filtering with size & aspect ratio, | n/a | | 70% DR and 0.2 FPR 127ms (8frame/s) |

Zhu et al. [10] improved the Dalal and Triggs approach by integrating a cascade-of-rejecters approach with the HOG features of variable-size blocks in order to achieve a fast and accurate human detection system. This has speeded up to 70 times, while maintaining an accuracy level similar to the Dalal and Triggs approach [8]. Instead, as mentioned in [11], the HOG features are constructed from 10062 blocks at multiple types, sizes, and locations. The system automatically evaluates one or more orientations to each block, which were based on local image properties located in the last module.

After features are extracted from each image, some classifiers for supervised learning such as Neural

Network (NN) or Support Vector Machine (SVM) or AdaBoost (known as learning-based methods) are then used to classify objects based on sample data. Discriminative classification techniques aim at determining an optimal decision boundary between pattern classes in a feature space. In *2010, Henry and Peters* [12], explained thatNeural Network (NN) is applied to many research fields; it is an effective tool to image classification and recognition. Whilst, SVMs learn the hyper plane that optimally separates humans from background in a high dimensional feature space. Its main advantage is that data used in SVMs can be of any type, e.g., scalar values or multi-dimensional vector features. However, human detection systems based on SVMs algorithms have enormous computational load. Some approaches have been developed to fast detection speed of SVMs.

As shown in [13], the multi-dimensional nature of the descriptor, to find an optimal linear classifier would require much longer time. Therefore, it is possible to use linear support vector machines (SVMs) as weak classifiers. However, to train SVMs could be time-consuming. In order to obtain a classifier for front, rear and side viewed humans Ger´onimo et al. [14] use a Real Ada-Boost learning method to select the best features among a set of Haar-wavelets and Edge Orientation Histograms (EOH) that cover all possible scales of a ROI. In J. Ge [15] mention that learning-based approaches are more favourable than rule-based methods (e.g., template matching and the shape-independent method), whose accuracy is limited by the difficulties in exactly translating all human knowledge into executable explicit rules.

## 4 DISCUSSION

Summarizes of human detection for surveillance systems which based on functions of them, distinguished by image sensor type, methods of ROIs generation and object classification, and detection performance, asshown in table 2, 3, and 4. The detection success of a system must be measured, but its computational requirements are also important. Mostly papers in this table discuss on performance evaluation of human detection systems, and Receiver Operating Characteristics (ROC) Curves are used frequently. Although they use different techniques and methods for presenting of results. Some of them have achieved promising results, where their detection rate is around 70-98 present. The ratio of successful detection of total human frame is detected from the total number of frames they appear. The false positives rate is the number of false detection in the total amount of frames.

Real-time infrared human detection by mobile platform will depend on a strong detection algorithm for use of computer resources. ROI generation is best achieved by a combination of techniques outlined, all with low computation. The supervised learning technique is not suitable classification methods, because they require too much memory and processing power for mobile platform applications. But very recently, as mentioned in [16], development of the low-cost systems, which may be the new style, and have drawn increasing attention.

Overall, the main difficulty for the detection and tracking of all systems involving multi-target tracking is the problem of occlusions. To solve this problem, as mentioned in [17], the approach to detect occlusions using a machine learning classifier for pairwise comparison of the people. Most researchers found that the final classifier learned by AdaBoost algorithm based on the thermal characteristics give better results from the classifier using the features of colour, but in combination with thermal characteristics and colour characteristics has produced the best classification performance. Moreover, with the incorporated the occlusion detection classifier into the detection algorithms, it will produce a significant improvement in overall system performance.

Finally, Thermal sensor not only solves the problem of detection, but can work in the darkness as possible, and it is particularly important in security applications. Furthermore, It can also be used for other tasks such as localization and object recognition tasks.

## 5 CONCLUSION

Security surveillance system is a key system to prevent the invasion, in areas such as banks, airports, warehouses, manufacturing plants, etc.. In fact, institutions like the military and police also depends on these systems. Since the invasion often occurs at night, then monitoring need to be addressed by using a system equipped with an infrared camera application. However, to develop this system is not an easy task to solve problems such as real-time tracking of the target change in uncontrolled outdoor scenarios. Though many works have been produced but there is no attempt to compare the work of each other. We have reached the point where a review of the state-of-the-art can help to summarize all the work done to this point.

The focus of conclusion is that in the last decade, there is a large research effort in human detection automatically. However, it can feel that we are still far from developing a system that is ideal. It is clear that significant progress was made in the classification of the candidates, mainly due to the synergy with generic object detection and applications such as face detection and surveillance. However, there are continuous efforts to do this research, while not yet reached a useful level of performance and the present surveillance system can be installed in applications such as Robotics Security Guard, police equipment / troops, vehicles, etc.Finally we have argued that the responsibility must be shared between tasks such as ROI generation and classification of objects. Of course we are confident about future performance in this research field.

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