# Thermal / Visible Stereo Vision for Electric Power Systems Autonomous Monitoring Systems

by F. Calado*, W. Ursine*, G. Teixeira**, H. Diniz**, P. Resende***, R. de Andrade****

*Postgraduate Program in Electrical Engineering – Universidade Federal de Minas Gerais - Av. Antônio Carlos, 6627, 31270-901, Belo Horizonte, MG, Brazil, wagnerursine@gmail.com, flavio.calado@ig.com.br
**Postgraduate Program in Mechanical Engineering - Universidade Federal de Minas Gerais - Av. Antônio Carlos, 6627, 31270-901, Belo Horizonte, MG, Brazil, guiemail@gmail.com , HENRIQUE.DINIZ@cemig.com.br
***Postgraduate Program in Electrical Engineering – Universidade Federal de Minas Gerais - Av. Antônio Carlos, 6627, 31270-901, Belo Horizonte, MG, Brazil,peterson@cpdee.ufmg.br
****Department of Mechanical Engineering – Universidade Federal de Minas Gerais - Av. Antônio Carlos, 6627, 31270-901, Belo Horizonte, MG, Brazil,rma@ufmg.br

**Abstract**

Thermography is a technique widely used for inspection of electrical equipment's operating conditions. However, its operation, predominantly manual, hampers more reliable diagnosis of component's abnormality indications. This paper presents a straightforward hybrid stereo vision configuration for autonomous monitoring systems that uses images visible and infrared spectrum to identify, characterize and extract regions of interest for increasing metrological quality of thermal measurements. Experimental results show that it is a viable and approach in asset management systems.

## 1. Introduction

Stereo vision computer systems based on visible spectrum are widely applied in various areas of knowledge. These systems are well accepted by offering good ability to extract features from objects of interest captured on the scene to a relatively low cost. They have been used, among many applications, for monitoring and diagnostic equipment [1], detection of obstacles [2] and quality control in production processes.

In power distribution systems, conductors, connectors, circuit breakers, surge arresters, transformers are subjected to thermo mechanical requests that compromise the quality of physical assets that need to have monitored their performance. Visual inspections may not reveal problems in performance, which become apparent only after serious incidents. In this context, Thermography allows one to verify the surface temperature without physical contact (safety) during full operation (no production loss) and in a short time period (high yield), while successfully identifying the potential failure points [3].

For these reasons, the technique has been employed in the construction of autonomous systems for failure diagnosis in electrical equipment. In autonomous systems of this nature, the definition of the physical limits of the equipment inspected, as well the intrinsic parameters of the infrared camera are critical steps for identification and fault diagnosis.

However, autonomous definition of region or objects of interest can be an arduous task because it is not always possible to ensure that is possible to distinguish the measurement object from another similar one, near or in the line of sight.

To assess this issues this paper presents a computer vision system that uses visible spectrum depth information to improve the acquisition and identification of objects processes to a thermal measurement. This approach is based on a calibrated two cameras stereo vision system, responsible for estimating the plans of each object in scene perform background subtraction and, through supervised learning algorithms, identifies them, and an infrared camera responsible for generating the images with the temperature of each point in its region of interest field of vision.

## 2. Hybrid Stereo Vision Systems

The first challenge of this work is to define the components of multispectral vision system for the acquisition. Pinto [7] presents a mobile robot for power substation hot spot monitoring. His paper proposes a single infrared camera unit connected to a robot which moves along the substation thought a steel cable inside the substation. Wang [8] presents a mobile robot for the same purpose with a two cameras vision system (one infrared and one visible camera) and an algorithm to equipment identification.

St-Laurent [5] presents an alternative using a visible / infrared stereo vision system based on pixels to pixel image combination to perform background subtraction in outdoor systems. This approach improves significantly the robustness of identification of regions of interest. However, as mentioned before, in high complexity situations, determining regions of interest in both images may cause non expected situations.

Lima [2], in his work, used disparity maps from an stereo vision system for pedestrian detection and obstacle avoidance for an autonomous vehicle navigation establishing distance, position and dimensions of any possible obstacle even in low light conditions. Krotosky [9] assess comparatively systems stereo vision in the visible and infrared spectrum detection using the same pedestrian avoidance performance comparison with disparity maps. However, those systems detect the presence and estimate the proximity without worrying about the accuracy of the shape of the obstacle.

So, to get advantage on benefits of visible imaging, this paper proposes a three camera arrangement with two visible cameras and one infrared camera. The visible cameras are responsible to extract object colors and textures and also estimate object's depth for background, and, why not, foreground subtraction.

### 2.1. Stereo Correspondence and Disparity Maps

Stereo correlation relays on the fact that a stereo vision systems can, by correspondence between each image, such as images (a) and (b) of figure 1, identify the distance between each of the pixels from each camera, considering that both are visualizing the same scene. This distance is called the disparity. The disparity map is the set of differences for each pixel for each pair of images [6] of the camera as seen in figure 1 (c) and (d).

The process involves identify, in both images, regions with higher similarity. This approach is called block matching. The value of the gap varies with the inverse distance from a point in space. In the correlation process there are some pixels which have no correlation between the images. It is caused by regions in the scene there are not captured by both cameras. These regions are marked on the map with a zero gray scale value forming areas of absence from the scene. These regions are called occlusion zones and its representation may be seen in figure 1 (e).

It is important to understand that a disparity maps gives one the opportunity to evaluate depth and distance references from objects in scene. The relationship between depth and disparity between two points in two diferent cameras is given by:

$$Z = \frac{fT}{x^a - x^b} \tag{1}$$

Where:
$Z$, is the disparity between two points in camera *a* and camera *b*
$x^b, x^a$: is point in camera
$f$: is the cameras focal length
$T$: is the *camera a* and *b* optical center distance to each other

Since depth is inversely proportional to disparity, there is obviously a nonlinear relationship between these two terms. So, closer an object is to the vision system, greater its disparity is.

For best understanding disparity values are commonly normalized as gray scale level color. This allows one to, instantly, visualize how closer objects in scene is from the vision system. In section X.X this will be extremely helpful to this paper algorithm.

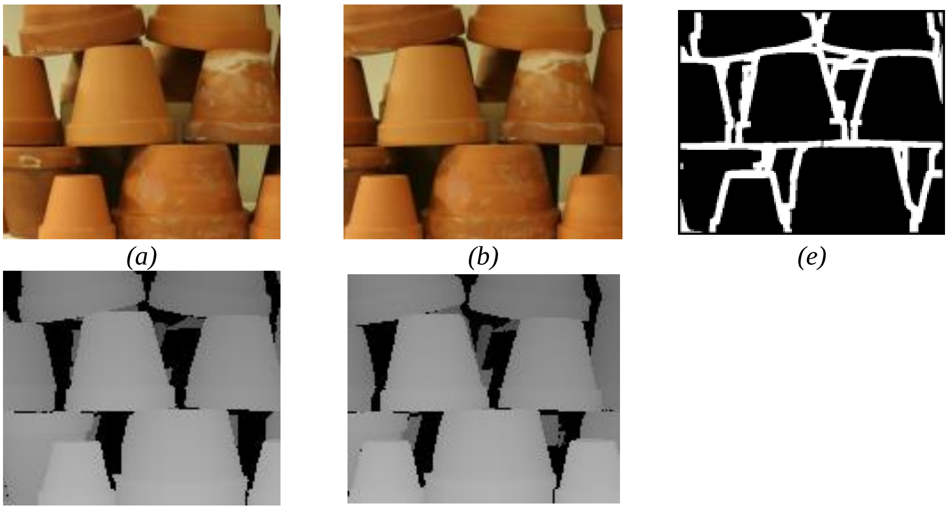



***Fig. 1***. *Stereo Vision Systems where (a) camera image right (b) Left camera image (c) disparity map right (d) disparity map left (e) merged boundaries of occlusion.*

### 2.2. Hybrid Stereo Calibration

Calibration can be defined as the calculation of intrinsic and extrinsic parameters of a camera. Such parameters are determined by means of calibration rigs with known characteristics [6]. However, this process is relatively new for hybrid systems and requires some important adaptation points. One fundamental point is the use of a calibration rig that provides high thermal and visible contrast, allowing its distinction in both spectrums.

Once the set of common points is known pixel-by-pixel alignment of these two images can be performed. It is possible to determine the difference in magnification and field of vision (FOV) besides the relative position between corresponding elements of this set. Figure 2 illustrates the difference between the fields of view of two cameras, highlighting the regions that are not entirely displayed on both images.

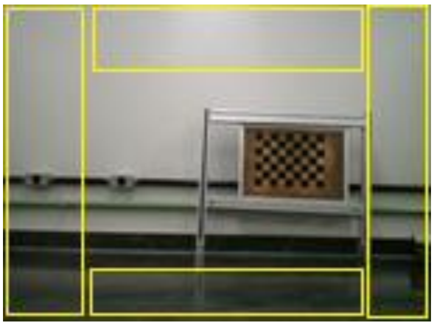
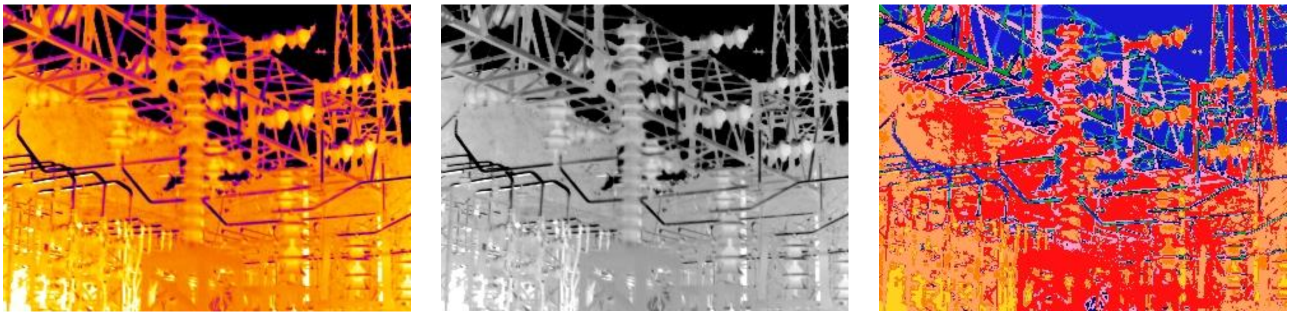


***Fig. 2.*** *Visible and infrared images Field Of View difference*

### 2.3. Image Segmentation and Feature Extraction

Infrared image segmentation is a well-researched topic. However, although great results achieved, its use as an exclusive information source is limited since thermal images have no commitment to object shapes. In electrical distribution environment, this is an important factor because, besides the high component density, all them have the tendency to be in very close apparent temperature. In this scenario, even in high contrast infrared cameras pallets, is a difficult task to achieve a good segmentation results. This can be seen in Figure 3 where a surge arrester is represented in three different pallets, iron (a) gray (b) and medical (c).



*(a)* *(b)* *(c)*

***Fig. 3.*** *Thermal imaging of surge arresters in different pallets (courtesy of CEMIG S/A)*

Almeida [4] evaluated the effects of thermal profile of surge arresters for fault detection by using artificial neuro-fuzzy network directly on thermal image segmentation information. However, his work incurs in same problems of segmentation algorithm functionality. Xia, Sun and Li [10] applied a SVM *(Support Vector Machine)* to infrared segmentation and feature extraction tasks in generic supervised learning structure.

In substation environment the objects are known and they have limited kinds wide range approaches are not necessary. Instead, what is really necessary is to describe well the differences between them. For this purpose PCA (principal component analysis) was adopted to optimize the need of search to classification best fit. The goal of PCA is to represent data in a space that best describes the variation in a sum-squared error sense.

## 3. Methodology

The main objective is to assess how the captured images in the visible spectrum by a stereo vision system can improve the rendering process of the thermal images and detect objects of interest in scene. To achieve this point one has to address the background subtraction first to, them, try to identificate possible

### 3.1. Background Subtraction

To accomplish the background removal a few steps must be executed to, after the calibration process, remove background noise. The main steps of this algorithm can be seen in Algorithm 1.

**Algorithm 1: Background Subtraction**

INPUT:
$I_{cr}$ : right RGB image;
$I_{cl}$ : right RGB image;
$I_t$ : Infrared camera image;
$D_{min}, D_{max}$: depth range

01. INITIALIZATION: $I_{disp} := Zeros(W_{cd}, H_{cd});$
02. $I_{msk} := Zeros(W_{cd}, H_{cd});$
05. BEGIN
06. $I_{disp} :=$ DISPARITY$(I_{cr}, I_{cl})$
07 $D_{min} := Min(I_{disp});$ $D_{max} := Max(I_{disp});$
08. FOR ∀ $(x \in I_{disp})$ and $iterator := D_{min}$ to $D_{max}$
09. $I_{msk} := GROUP\ (iterator)$
10. IF $(Max$ (SIMILARITY $(I_{msk}, PATTERN))$
11 $I_{out} := (I_{out}) and (I_{msk})$
12
13 END

OUTPUT: $I_{tout}$: masked thermal image

This first stage of algorithm, represented by line 06, uses the correlation between the images of the vision system in the visible spectrum to estimate the limits of the plans and objects in the scene. In line 07 the disparity boundaries are taken as depth limits in image.

After this pre-set, the algorithm do a scan through image depths grouping, line 09 of Algorithm 1, clusters of pixels that apparent to be at the same or proximal depth. This operation is configured in design time when the system user determines

One advantage of this algorithm is that how it groups possible disparity pixels by their values, it is straightforward to choose not only the frontend pixels but, if its desirable, the background pixels. Hence, a possible variation of this algorithm could be a pre-set or a deliberate user chosen value who informs ranges of values.

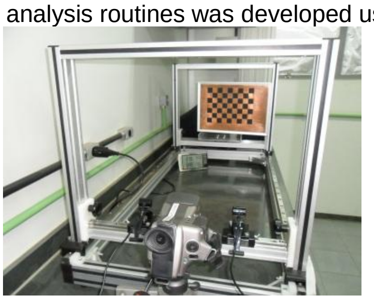
### 3.2. Feature Extraction and Pattern Classification

For feature extraction and classification tasks, a training database was created.before starting classification process., This knowledge base is structured with images, in visible spectrum, and relevant characteristics of substation equipment’s in a training phase. These images are acquired by the vision system and processed by a PCA (primary component analysis).

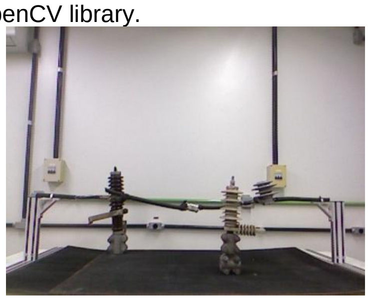
In classification step, described in Algorithm 1 lines 10 and 11, the image without background noise is vectorized and

## 4. Experimental Results

To test the methodology, a low cost stereo vision system prototype was built with two SPN230NC Phillips webcams and a Flir P20 infrared camera Fig. 4(a) and a small test bench Fig. 4(b). All pre-processing, calibration and metrological analysis routines was developed using the free GPL C++ OpenCV library.



(a)

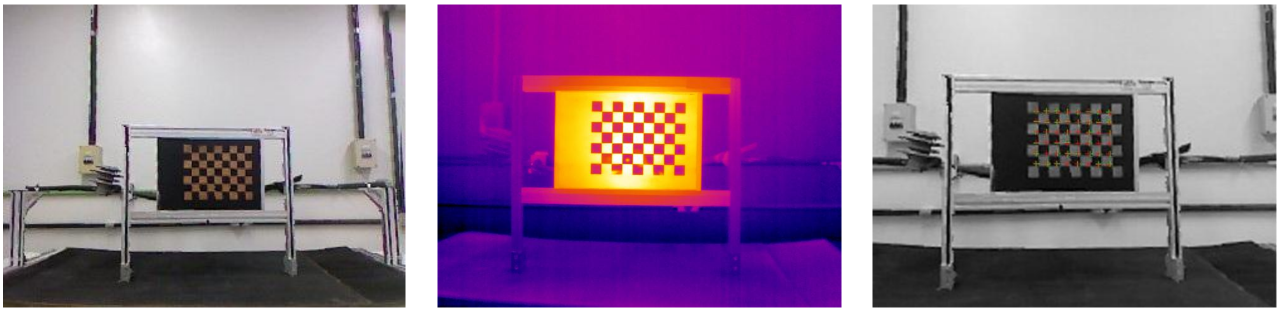


(b)

***Fig. 4.*** *Stereo vision system prototipe (a) and test bench (b)*

### 4.1. Hybrid Stereo Calibration Procedure

The calibration rig was positioned on test bench and both visible and infrared images were captured with a artificial heating procedure up to 35°C. In this procedure, magnification and lens distortion were compensated and the field of view was compatibilized with infrared camera. This can be seen in fig. 5 where clearly visible camera field of view fig. 5 (a) is wider than infrared camera fig. 5 (b). The result is an corrected image with about infrared camera field of view fig. 5 (c).

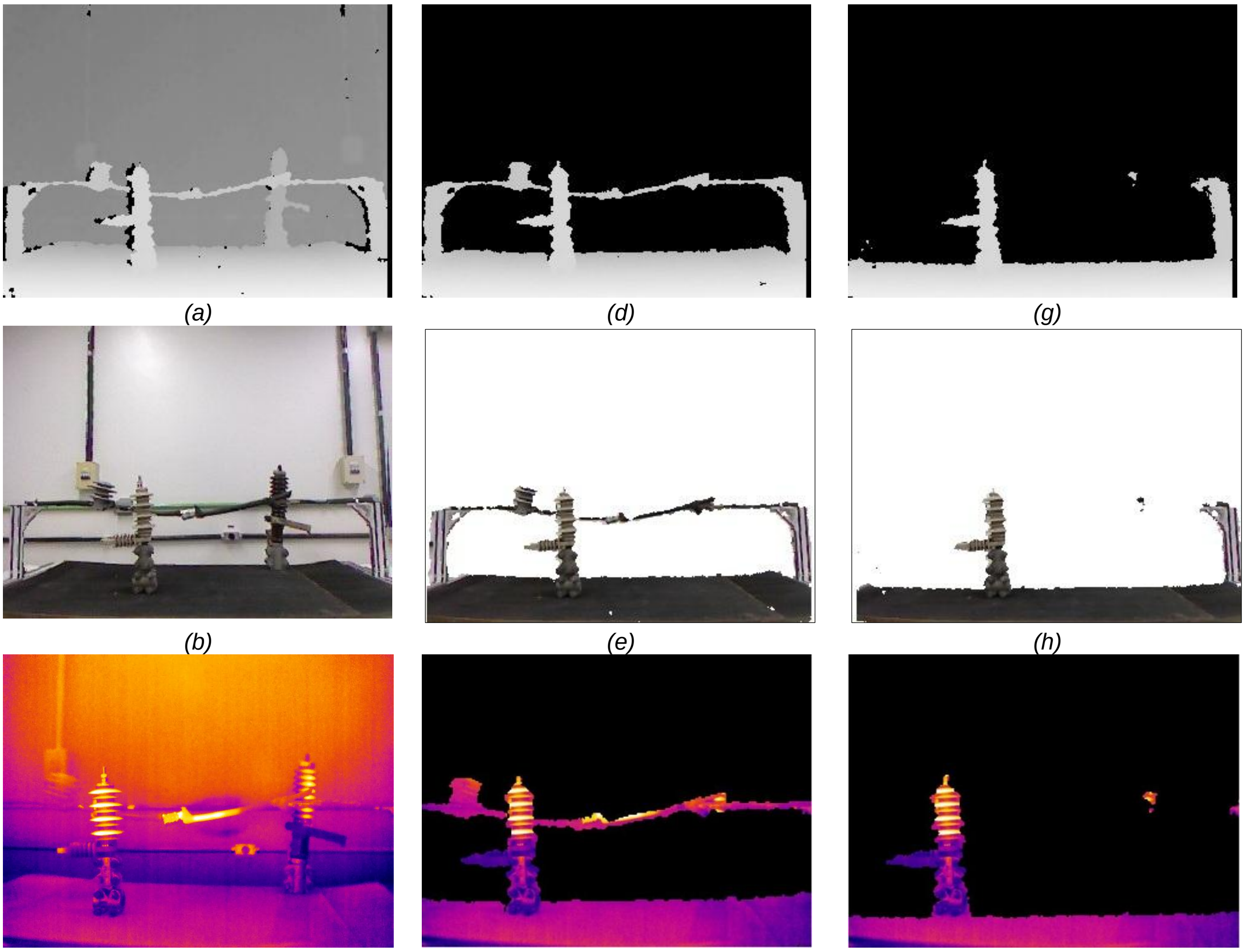


*(a)* *(b)* *(c)*

***Fig. 5**. Calibration Rig: 320x240 resolution visible (a) 640x480 thermal image (b) reprojection of calibrated points (c)*

### 4.2. Background Subtraction

In test bench, four substation components were mounted simulating a common arrangement. Were used two different types of surge arrester, one insulator and a connector. This arrangement was intentionally made to overlap the vision system line of sight. For each algorithm iteration, the correspondence between visible, depth and thermal image was done. These components were positioned at 3 meters from the stereo vision system. Results can be seen on fig. 6.

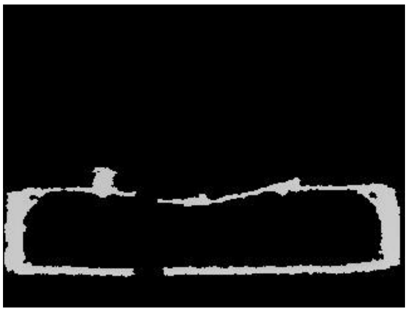


*(c)* *(f)* *(i)*

***Fig. 6**. Segmentation Results for background subtraction (a,b,c) rgb, segmented and thermal first iteration: depth value = 0 (d,e,f) second iteration: depth value = 10 (g, h, i) third iteration: depth value = 16*

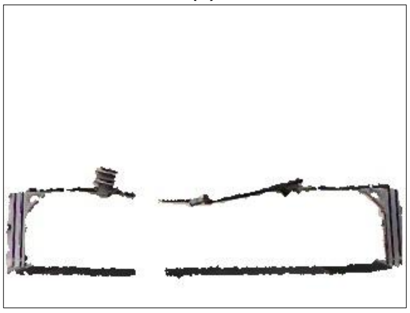
This results show that the calibration between thermal and visible cameras really achieved good operational parameters. However, comparing with thermal image, one can see that the final segmented image has some information loss in object boundaries. This occurs because disparity maps cluster are surrounded by occlusion zones and its variations could invade the object area.

For evaluate the robustness of the algorithm, arbitrary range of values of depth were selected to verify the possibility of detect background omitting the image frontend.

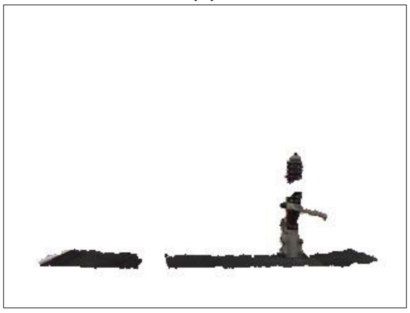


*(a)*

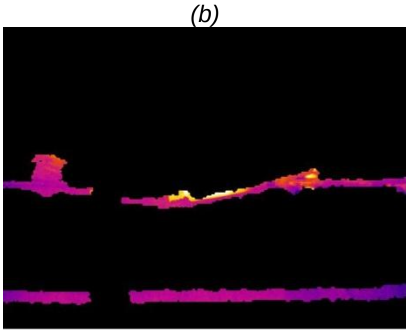
*(d)*



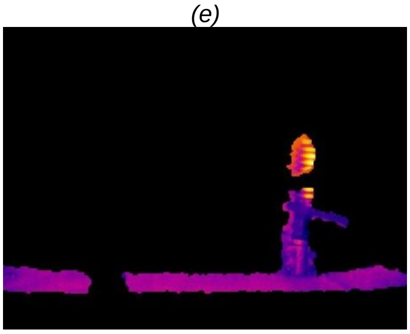
*(b)*



*(e)*



*(c)*



*(f)*

***Fig. 7**. Segmentation Results for background subtraction (a,b,c) rgb, segmented and thermal first iteration: depth value = 0 (d,e,f) second iteration: depth value = 10 (g, h, i) third iteration: depth value = 16*

This results show that is also possible to identify object there are not in first plane in image. In fig. 7 one can realize that the last surge arrester, fig. 7 (f), was separated from all the other objects in image. It is especially interesting for this work purpose because, in electrical inspections applications, sometimes it is impossible to have a clear line of sight to target. Another interesting point is that the segmentation process succeeded in not to miss the cable, connector assembly.

The last evaluated task is object identification. During image segmentation and acquisition, three samples from each object of interest were copied from segmented images. These samples, fig. 8 (b), represent each component and were used to create the knowledge base to PCA algorithm. Each class was analyzed and their separability can be seen in fig. 8 (a).

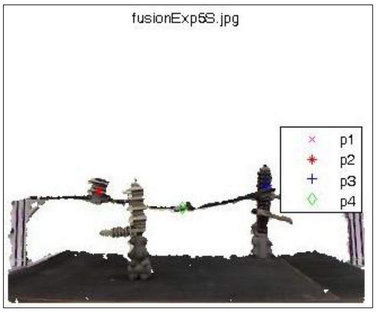
In a first analyze, these samples do not succeeded in trace a good line between those classes. In fact, in validation step, its performance was reasonable, fig. 9, but improvements could be achieved with a larger scale sample database. So, it will be foolish to think that this methodology does not work to this purpose;

http://dx.doi.org/10.21611/qirt.2012.268

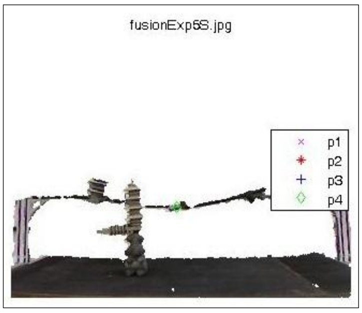


(a) (b)

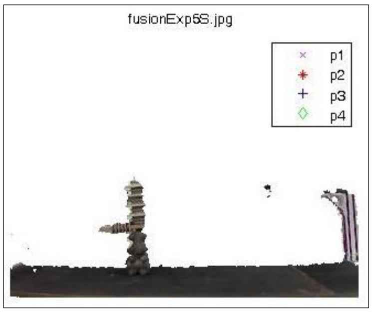
***Fig. 8.*** *Training PCA separation result in substation components database (a) visible an thermal templates for dimensionality reduction*



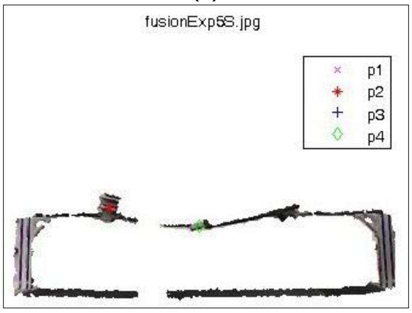

(a)



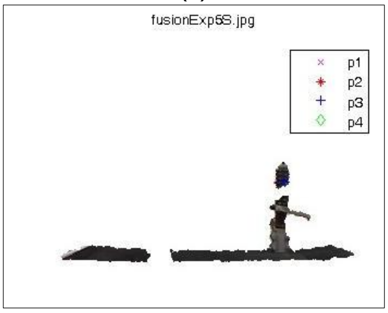

(b)




(c)




(e)




(d)

***Fig. 9.*** *Testing PCA classification*

## 5. Conclusions

This paper presents a computer vision system that uses visible spectrum depth information to improve the acquisition and identification of objects processes to a thermal measurement. This approach is based on a calibrated two cameras stereo vision system, responsible for estimating the plans of each object in scene perform background subtraction and, through supervised learning algorithms, identify them.

In the first matter, background subtraction, this approach showed itself very useful. It succeeded in remove background noise as removed image frontend object. This capability could be used in a wide range of applications and it is especially interesting for autonomous thermal systems. Thermal / visible calibration procedure is a useful technique as well.

Some improvement should be made to avoid loss of information caused by near boundary disparity value variation. A viable solution is to add a confidence offset allied with a post process image segmentation to refine a slightly wider than the measured object.

In pattern recognition matter, it is necessary a larger scale database to perform a good training procedure. Only then, a methodology could be evaluated.

It is a fact that exclusive use of infrared images to detect regions of interest for analysis practice is not advisable in view of the object boundary. Thus, this work, as mentioned, shows relevant as their approach. The proposed methodology shows that it is possible to create hybrid environments that allow the relatively low cost, a considerable improvement in the sensitivity of infrared equipment acquisition. Furthermore, it has proved very useful for the process of determining the regions of interest.

**REFERENCES**

[1] Silva, L.; Petraglia, A.; “Sistema de Visão Estéreo Para Inspeção Submarina de Tubulações e Equipamentos de Petróleo em Águas Profundas”; SEMINÁRIO DE AUTOMAÇÃO E AUTOMAÇÃO, INSTITUTO BRASILEIRO DO PETRÓLEO, 1998

[2] Lima D.; “Navegação Segura de Um Carro Autônomo Utilizando Campos Vetoriais e o Método da Janela Dinâmica”: Dissertação de Mestrado; Programa de Pós-Graduação em Engenharia Elétrica da Universidade Federal de Minas Gerais, 2010.

[3] Teixeira, G.; Gomes Jr., C.;*et all.* “Avaliação De Incerteza De Resultado De Medição Em Termografia Infravermelha Pelos Métodos Gum E Monte Carlo, Aplicada Ao Diagnóstico De Conexões Elétricas”; CONGRESSO IBERAMERICANO DE ENGENHARIA MECÂNICA, 2011.

[4] Almeida, C.; Braga, A., Caminhas W. *et all*; “Intelligent Thermographic Diagnostic Applied to Surge Arresters: A New Approach”; IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 24, N$^{o}$ 2, Abril 2009;

[5] St-Laurent, L.; Prévost, D. e Maldague, X.; “Thermal imaging for enhanced foreground - background segmentation”;

[6] Bradski, G., & Kaehler, A. “Learning OpenCV – Computer Vision with the OpenCV Library”. O’Reilly Media, 2008.

[7] J. K. C. Pinto; M. Masuda; J. A. Jardini; “Mobile robot for hot spot monitoring in electric power substation;”

[8] Wang B., Guo R., Li B., Han L., and Sun Y. “SmartGuard: An Autonomous Robotic System for Inspecting Substation Equipment”

[9] Krotosky S. J., Trivedi M.; “A Comparison of Color and Infrared Stereo Approaches to Pedestrian Detection”; IEEE INTELLIGENT VEHICLES SYMPOSIUM, 2007.

[10] Jiyin Sun, Jing Xia, Hui Li, “Segmentation of Infrared Image Using Support Vector Machine”