

# SPATIAL LOCALIZATION OF INFRARED RADIATION SOURCES USING PYROELECTRIC SENSOR SYSTEMS

Alexandr Knápek

Master Degree Programme (2), FEEC BUT  
E-mail: xknap03@stud.feeec.vutbr.cz

Supervised by: Jiří Majzner

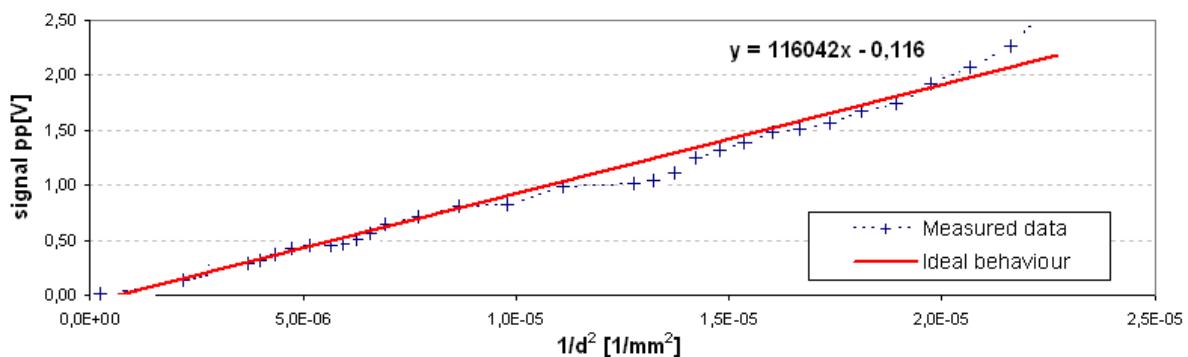
E-mail: majzner@feec.vutbr.cz

## ABSTRACT

The objective of this study is to develop the system, which would be able to localize an infrared (IR) emitting source located somewhere in the space between the installed pyroelectric sensors. For this purpose, classical localization methods could be used as well as the artificial neural networks (ANN), which are becoming still more popular these days. The system is able to detect the exact placement of the IR radiation source. This system could be used for example in aircraft industry, where every plane is checked for the presence of some superheating or local fire, or for oil tank control or for like human body detecting.

## 1. INTRODUCTION

All objects with a surface temperature above absolute zero emit thermal or infrared radiation (IR). The warmer an object is the greater amount of energy emitted. The hot object emits not only infrared radiation, but also visible radiation known as short wave radiation. *Pyroelectricity* is an electrical potential that is generated in certain materials when they are heated. The change of the temperature, makes the positive and negative charges move to opposite ends through migration, and hence, an electrical potential is established. Our sensor is based on the LiTaO<sub>3</sub> (lithium tantalate) crystal which generates a surface electric charge when exposed to the IR radiation.



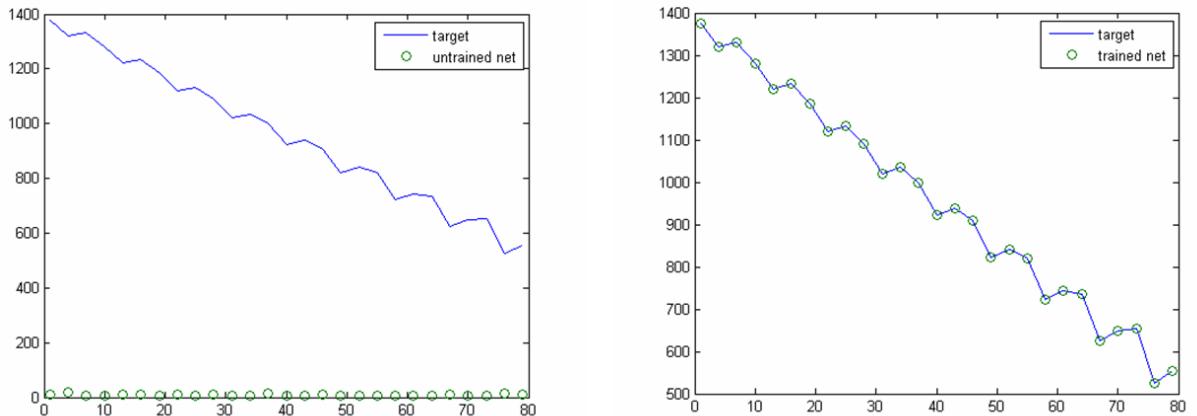
**Figure 1:** Detector's functional dependency on the distance of the IR source

## 2. PYROELECTRIC SENSORS PROPERTIES

Pyroelectric infrared sensor (sometimes referred as PIR) is the basic part of our measurement installation. Its main property, intensity of the output signal, is related to the distance from the IR source (Bunsen burner has been used as the referential source). From our measurements, we can see that the detector's output intensity is inversely proportional to the square of the distance from the source of infra-red radiation, simply the output characteristics follows the ***inverse square law*** (Fig. 1). This is very important for the analytical source localization, where the sensor's output characteristics can be very simply substituted using suitable linear function. When using the ANN, the knowledge of the characteristics is irrelevant, because the ANN approximates it from the net's learning data.

## 3. EXPERIMENTAL SETUP

The installation for obtaining the training and testing data consists of four PIR sensors. Every PIR detector is placed in the middle of the detection area's side, which has rectangular shape. A standard laboratory Bunsen-burner is used for obtaining the training data. Signal intensity values are measured for the grid of 9x9 burner's positions for each sensor, so the training data for the one position consists of 4 voltage levels (each for one sensor) and desired data of 2 coordinates. This matrix is used not only for the neural network training and testing, but also as input data for the *Method of Circles*. With knowledge of the *functional dependency* of the detector's intensity on an IR source distance, we are able to compute the estimate source's coordinates using conventional mathematic analysis, namely the Method of Circles. The distance from each detector is computed from the regression equation, which is shown on the Fig 1. Inaccuracy is caused due to the non-ideal output behavior and due to the presence of sensor's own noise which distorts our measurement.



**Figure 2:** Performance graphs of the a) untrained and b) trained network

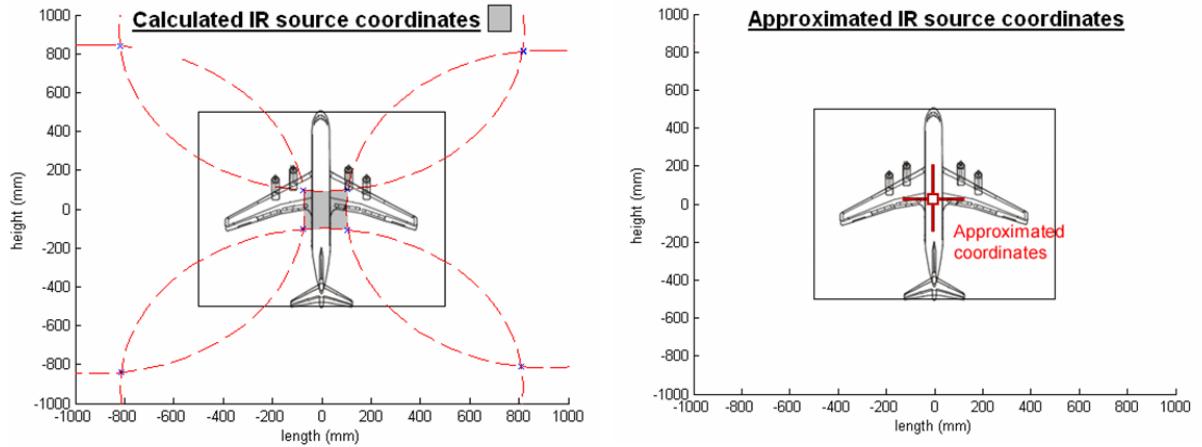
Better results are achieved when using the neural-network approximation. Our network is of a cascade-forward topology with *Levenberg-Marquardt* training algorithm. There are four neurons in the *input layer*, where each process one value of each PIR detector. On the *output layer*, there are two neurons, which provides the X and Y coordinates for the IR source location. Between input and output layer, there are three *hidden layers*, based on sigmoid transfer functions. The network is trained for the performance of 0.0108795 (where the goal is zero) in only 120 *learning epochs*.

#### 4. LOCALIZATION OF THE IR SOURCE

At first, we will show algorithm of localization using conventional mathematic method called *Method of circles* (MOC), which improves the triangulation method in principle (Fig. 3a). The localization approach is very simple, at first a *distances* from the single detectors are computed from the knowledge of the *functional dependency* of the detector's intensity  $u$  on the burner's distance as mentioned before (Fig. 1), where the diameter of the circle  $r$  (according to the input voltage) is:

$$r = \sqrt{\left(\frac{116042}{u + 0,116}\right)} [\text{mm}] \quad (1)$$

When there are all the diameters computed (for every detector's range), circles are drawn (computed) and their intersection is designated (Fig. 3a).



**Figure 3:** Comparison of the localization accuracy using a) MOC b) ANN

Second approach is based on *generalized multilayer perceptron* (MLP) which is learned under the supervision (Fig 3b). This form of learning assumes the availability of a labeled set of training data made up of  $N$  input – output examples. Both methods' results are shown in the Fig. 3. Here you can see, that when using the MOC algorithm, only approximate estimation of the source placement can be made, in comparison with the ANN approximation that gives us the exact coordinates.

#### 5. CONCLUSION

The two localization algorithms of IR source have been presented. Neural network's main advantage is, that we don't need to know the detector's functional dependency (because this is will be approximated by the network herself). The ANN also returns exact coordinates, not only estimated area. Usage of the detectors with various window filters can extend this application for a wide range of applications (human body detection for example).

#### REFERENCES

- [1] Irwin W. Sandberg, et al., Nonlinear Dynamical Systems: Feedforward Neural Network Perspectives, Wiley and Sons - December 2000 ISBN: 0471349119