

Image processing of infrared thermograms for hidden objects

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Abstract – In this paper an approach with the flowchart of infrared image processing for hidden objects detection is proposed. The shown results are only referred to the buried mine detection. Because image processing available so far can not detect 100% of hidden subsurface objects it is necessary to combine different technologies to enhance the detection rate.

Keywords – Infrared image processing, Thermography, Hidden subsurface object detection

I. INTRODUCTION

Thermography technique for non-destructive testing is used successfully for the detection of materials discrete defects and the estimation of material properties without causing changes of their performance. Except numerous applications of infrared thermography testing in civilian industry they have found a wide use in rocket, aircraft industry and in military applications. Typical technical objects of non-destructive testing are among other things all types of materials connection (welded, soldered joints etc.) and also constructions and elements made mainly from composite materials.

Hidden object imaging by thermography can be widely used in many application fields, including video surveillance and monitoring, scene understanding, tracking objects and object recognition [1]. However, the major limitation of this approach is that the infrared camera can only get the roughly contour of the object, which is not enough for further image analysis. Infrared detectors are passive sensors that create infrared, or thermal, images without having to expose the subject to any radiation. These images show the heat signature that is given off by objects of interest. Two applications are taken into account buried mine detection or concealed weapon under clothing detection. In the paper are shown only results of mine detection experiments, but analogous approach can be used in the other case, too.

Thermographic inspections produce large amounts of information with infrared images and reports that contain data such as environmental conditions during the inspection, inspected component conditions, data from the operator, etc.

Various methods of data analysis particularly suited in thermography testing have been developed through the World. It is interesting to notice that besides traditional techniques

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coming from the field of “computer vision” imported into specific available camera’s software several specific methods have been developed for thermography testing. These unique techniques are sometimes based on the underlying heat-conduction physics [2]. In the paper, the discussion and implementation of the methods at image processing of infrared thermograms in specific area as hidden objects: buried mines and hidden weapon under clothing detection.

II. EXPERIMENTAL SETUP AND PREPROCESSING

The test minefield was a box of soil (sandy or clay). To measure soil surface temperature, an infrared (IR) camera ThermoCam Sc640 was fixed above the minefield. During the experiment, the measured data were collected for processing. The temperature resolution of the camera is 0.08°C. Moreover, the data such as air temperature, wind speed and sky irradiance were measured during the experiments. In the experiments are used objects with cylindrical shape equivalent to the shape and dimensions for some type of AP mines with plastic and PVC materials. On the Fig.1 is shown the experimental setup for thermography mine detection.

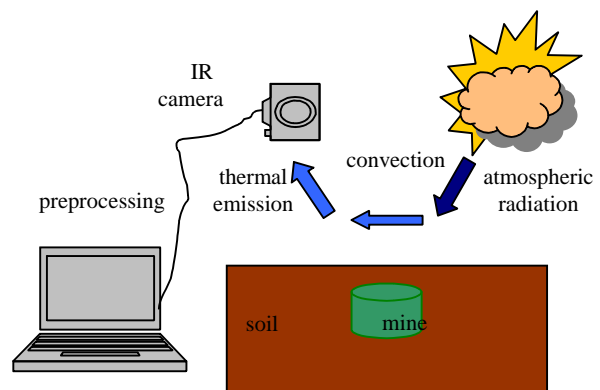


Fig.1. Experimental setup and different heat transfer processes for thermography mine detection

Before applying the algorithms to the thermograms set, a pre-processing procedure, consisting of radiometric calibration, temporal co-registration, environment correction, apparent temperature conversion and inverse perspective projection was applied to the acquired thermograms sequence.

The previous tests [3] for mine detection have indicated that it is not easy to determine accurately the real sizes of different objects buried at different depths. In a single image sequence with usual anomaly detection techniques such as neuron network, mathematical morphology it can even be lose objects whose thermal signature are dominated by others [4].

For example the environment correction is used for estimating the attenuation of the radiated thermal energy through the path from the surface to the camera. After environment (atmospheric) correction, the resulting radiance is an estimation of the radiance originated from the surface. This radiance consists of two components: the radiance due to emission from the objects having a temperature above 0K and the accumulation of all the reflections of the objects in the direction of the camera. Since the examined objects are not blackbodies, then their temperature can still be approximated by so-called apparent temperature. Ground projection maps the IR images onto the surface of the soil producing thermograms (with a resolution of 1 cm²/pixel) sequence of the soil surface apparent temperature.

The preprocessed thermograms used in the following represent the soil surface temperature.

III. NONDESTRUCTIVE INSPECTION

The solution of the forward problem F is the solution of the Heat equation. Lets y is measured data and p is the original distribution of parameters that gives rise to y under the application of operator F . In our case p corresponds to the value of the thermal diffusivity at every point within the soil volume α . So the functional equation involving a map F , which represent the connection between the model and data is

$$Y = F[p] \tag{1}$$

where $F[p]$ is the distribution of the temperatures of the surface of the soil.

An inverse problem of this will be the reconstruction of the original distribution of parameters based on measurements of the resulting data. Solving an inverse problem implies approximating the best solution

$$p = F^{-1}[y]. \tag{2}$$

In general y is never known exactly but up to an error of $\delta \neq 0$. It is assumed that we know $\delta > 0$ and

$$\|y - y^\delta\| \leq \delta \tag{3}$$

So y^δ is the noisy data and δ is the noise level. To compute numerically a solution of the problem it can be used the regularization techniques to restore stability and existence of the solution and develop efficient algorithms.

IV. TARGET DETECTION

Using thermal infrared images to detect subsurface hidden objects is based on the assumption that these objects have different thermal properties than their surrounding area. When an area is heated, the hidden objects will warm up faster or slower, because of the thermal properties of the materials. The influence of the hidden object on the temperature at surface level relates to the distance from the surface. This situation, where hidden objects give relatively warm spots at the surface, is called a situation with positive contrast. For this

reason, and under natural heating conditions, sunrise and sunset are the times of the day at which this thermal contrast is largest.

It is assumed that a pre-processing stage is run on a conventional PC in order to align the images and map grayscale colors to temperature values on the surface. Next, the soil inspection procedure itself starts. First, a detection procedure is run to obtain the mask of potential targets. Then, a quasi inverse process operator is used to identify the presence of mines among the potential targets. For those targets that failed to be classified as mines (and are therefore labeled as unknown), a full inverse procedure to extract their thermal diffusivity will be run in order to gain information about their nature. The overall detection process is summarized in Fig. 2, where the processes that require the use of the 3D thermal model are indicated with an ellipse. The detection, quasiinverse and fullinverse procedures are based on the solution of the heat equation for different soil configurations. As explained, this is a very time consuming task that makes the whole algorithm inefficient for real on-field applications.

The use of IR cameras taking images of the soil under inspection gives the exact distribution of temperatures on the surface. On the other hand, the thermal model described previously and extensively validated with experimental data permits to predict the thermal signature of the soil under given conditions. The detection of the presence of potential targets

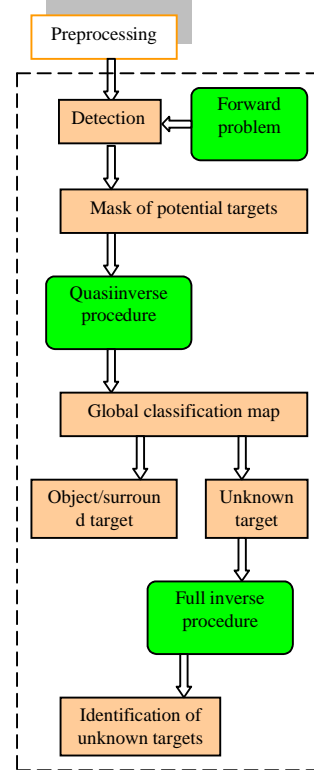


Fig. 2. Structure of the approach to detect hidden objects

on the soil is then made by comparing the measured thermograms with the expected thermal behavior of the soil given by the solution of the forward problem under the assumption of absence of mines on the field.

The surface positions (x, y) are determined where the behavior is different from that expected under the assumption of mine absence, therefore revealing the presence of unexpected objects on the soil. These positions will be classified as potential targets, whereas the rest of the pixels (those that follow the expected pure-soil behavior) will be automatically classified as soil. This process is not trivial.

The most straightforward approach, the threshold detection, has the drawback of setting the threshold, which will vary not only for different image sequences, but it is also likely to depend on the particular frame of the sequence, and on the characteristics of the measured data such as lighting conditions and the nature and duration of the heating. For this reason, the use of a reconfigurable structure, capable of adapting to varying experimental conditions was proposed on [5]. In this work it is demonstrated that it is possible to reduce the time frame of analysis when the maximum thermal contrast at the surface is expected. This phenomenon can be better appreciated in Fig. 3, where a sequence of IR images of a mine field taken between 18:50 am and 19:50 pm is shown. Taking into account the short time interval we can consider that the properties of the soil remain unaltered and that there is no mass transference process during the simulation. The output of the detection stage is a black and white image with the mask of the potential targets.

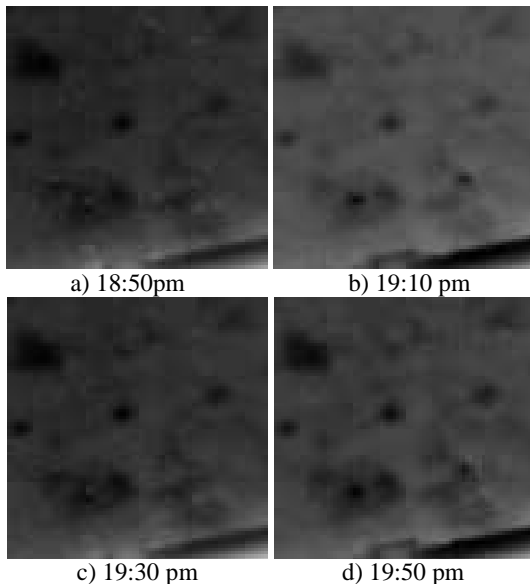


Fig. 3. Example of measured thermograms of minefield at sunset

V. CONCLUSION

Two techniques to reduce the computing time can be used. The first one is an FPGA implementation of the thermal model that speeds up the computations making the system suitable for field work applications. A scheme of the algorithm where the FPGA system can be realized is proposed. The processes makes use of the thermal model, running on the FPGA, are indicated with dashed points. The second approach consists on using non-uniform grids to reduce the number of nodes involved in the computations and therefore, the computing time. The FPGA implementations will be fully realized in recent and presented in some other report.

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