Radiometric Model for the Infrared Signature of a Land Mine Buried Under a Rough Surface

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Abstract

A radiometric model is presented for the infrared (IR) signature of a buried land mine. The soil surface temperature is predicted with a finite element method (FEM) based thermal model previously described by the authors. Enhancements to that thermal model are presented including a rough surface description of the soil-air boundary. The radiometric model addresses both the spatial and spectral characteristics of the soil. The atmospheric propagation modeling code MODTRAN is used to predict the intensity and spectral dependence of the incident radiometric components. Simulated IR imagery is presented for land mines buried under both smooth and rough surfaces. The effects of random surface emissivity variations are also demonstrated. Validation of the combined thermal-radiometric model is presented using experimental data. It is found that the signature shape and temperature contrast are fairly well predicted.

Keywords

Thermal infrared imagery, land mines, radiometric modeling, surface roughness, heat transfer, thermal modeling, numerical simulation, finite element method.

I. INTRODUCTION

In a recent work Sendur et al. [1] described a FEM based three-dimensional thermal model to predict the soil surface temperature over a buried land mine. That model is capable of simulating realistically shaped land mines and inhomogeneous soil. They presented the temporal evolution of the surface temperature for various mine types.

In addition to the mine’s thermal signature, an IR image of the surface will also contain undesirable reflected light from natural sources. The latter comprises a form of clutter, which has a detrimental effect on mine detection performance. Natural sources are also wavelength dependent, which requires attention to the spectral content of those reflected components. Therefore, to better understand the IR signatures of buried land mines and clutter, a spectral radiometric model is required. There has been little work in radiometric modeling of mine signatures. Flynn et al. [2] developed a surface mine simulation tool for the UV-VNIR regime, but no prior work on radiometric modeling for buried mines has appeared.

In this work we describe a radiometric model capable of predicting the IR signatures of buried land mines. The model addresses both the spatial and spectral characteristics of the environment. The work is organized as follows: In Sect. II we summarize some
enhancements to our FEM thermal model which permit more realistic modeling of the natural environment. The radiometric model is presented in Sect. III. The radiometric components of IR imagery are briefly discussed in Sect. III-A. Sunlight and skylight models are given in Sect. III-B, including their spectral dependence. The simulation of IR imagery is discussed in Sect. III-C. Numerical results for a cylindrical anti-tank mine are presented in Sect. IV. Examples of the temporal evolution of IR imagery for smooth and rough soil surfaces are given therein. Concluding remarks appear in Sect. V.

II. THERMAL MODEL IMPROVEMENTS

A buried mine affects the flow of heat flux into and out of the soil, since its thermal characteristics are different than those of soil. This alteration of the heat flow results in a disturbance of the surface temperature, which is the primary source of the IR signatures of buried land mines\(^1\). The authors have previously described a technique for calculating the soil surface temperature over a mine, which may be consulted for details [1]. As improvements to that thermal model, in this study we suggest two major modifications: (1) a rough soil-air boundary and (2) a more sophisticated model of the solar insolation.

Prior experimental work suggests that a rough soil-air interface has a strong influence on the clutter signature of soil. This roughness complicates the thermal modeling as a result of spatial variations in the absorbed down-welling solar radiance (via the variable local surface normal). Surface roughness also affects the calculation of the reflected sunlight and skylight, which arises in the radiometric model discussed next. A rough surface is easily incorporated in our thermal model by varying the tilt in the triangular surface facets. A sample discretization of a volume is given in Fig. 1.

The second modification to our previous model is the incorporation of a more realistic solar insolation function. In previous studies we used a relatively simple analytic function that addresses the time of day, cloud extinction, atmospheric absorption, and soil albedo. That model employs atmospheric transmittance data given by Allen [3], approximated in a functional form by Watson [4]. In this study the more sophisticated capability provided

\(^1\)Other phenomena that may contribute to buried mine signatures include the difference in soil moisture content (and the concommitant change in soil emissivity and thermal properties) due to the moisture barrier formed by the mine. This barrier also affects the vitality of any overlying vegetation.
by MODTRAN [5] has been incorporated. MODTRAN provides several benefits including more accurate calculation of solar position for a given latitude and longitude and atmospheric modeling that includes the effects of absorption bands and weather conditions.

III. Radiometric model

As noted above, the IR signature of a buried mine includes various soil reflected components in addition to the thermal components, and the inclusion of those components is the principal contribution of this work. In this section we review the additional components and our models for them.

A. Components of the IR image

The radiative components seen by the IR camera include (1) thermal emission from the soil surface (a portion of which comprises the desired signal), (2) soil-reflected sunlight, (3) soil-reflected skylight (thermal emission from the atmosphere and sunlight scattered by particles and air molecules), and (4) a negligible amount of thermal emission from the atmosphere directly to the camera. These components are illustrated in Fig. 2, and we write the total radiance received by the sensor as

\[ L_{rec}(\lambda, r) = L_{surf}(\lambda, r) + \mathcal{R}(\lambda, r) [L_{sun}(\lambda) + L_{sky}(\lambda)]. \]  

In this work we model the soil surface as a diffuse reflector, which simplifies the analysis.

B. Sunlight and skylight models

Sunlight and skylight contribute to both the thermal and radiometric models. The short wavelength solar heating of the soil surface comprises the dominant source for the thermal model, and long wavelength reflected radiance is received by the IR sensor.

The radiance \( L_{SUN} \) can be modeled with reasonable accuracy by a blackbody radiator. Neckel and Labs [6] show that a blackbody source at \( \approx 5800 \) [K] represents a good numerical fit to exoatmospheric measured radiance data in the visible and near IR bands. Thekaekara and Drummond [7] summarized data regarding components of the total radiation and their spectral distribution, and they proposed standard values for them. Measured solar radiation at different sites and models for meteorological and climatic factors are presented
in a summary by Dogniaux [8] prepared for the European Community Programme on Solar Energy. The measurement techniques and instruments are described in Coulson [9]. Figure 3 (a) illustrates the predicted solar radiance at the outer surface of the atmosphere using a blackbody emitter at 5800 [K].

The atmosphere attenuates both the down-welling solar radiance and skylight and the reflected and emitted radiance. In many demining applications the distance between the IR camera and the soil surface is small and, hence, the attenuation of the down-welling solar radiance is of greatest concern. For airborne mine detection, attenuation of the emitted and reflected signals must also be considered.

Sophisticated modeling tools have been developed to deal with the complexities of the solar radiance and atmospheric transmission, absorption, and scattering phenomena. These models predict transmittance and radiance for sensor systems under varying atmospheric conditions. Among these computer codes, LOWTRAN (Low spectral resolution transmission), MODTRAN (Moderate spectral resolution transmission), and FASCODE (Fast atmospheric signature code) are commonly used. LOWTRAN is a one-parameter, band-model code that predicts atmospheric absorption and scattering for systems with low spectral resolution. It is computationally efficient, and it has an atmospheric database that can model six reference atmospheres with various constituents. MODTRAN is a two-parameter, band-model code with a higher resolution than LOWTRAN (2 cm\(^{-1}\) for MODTRAN versus 20 cm\(^{-1}\) for LOWTRAN). FASCODE is a high-resolution code, which is usually reserved for studies involving very narrow bandwidth.

To model the atmosphere we have selected the 1976 US standard atmosphere. Temperature, pressure and water-vapor altitude profiles, and altitude profiles of relevant gases (ozone, methane, nitrous oxide, carbon monoxide, and others) were set to values of the 1976 US standard atmosphere, but we set the CO\(_2\) mixing ratio to 365 ppmv, which is consistent with more recent data. The weather is assumed to be clear and sunny. To model boundary-layer aerosols, rural extinction was selected with a visibility to 23 km. (Visibility is related to aerosol extinction at 550 \(\mu m\).) Figure 3 presents the solar spectral radiance at Columbus, OH on April 3. Figures 3 (b)-(f) show the solar radiance predictions with atmospheric effects at 10AM, 12PM, 2PM, 4PM, and 6PM, respectively.
The quantity $L_{SKY}$ depends on the composition of the local atmosphere and is more difficult to measure. It comprises wide-angle Rayleigh scattering by molecular constituents (very weak at IR wavelengths), small-angle Mie scattering by aerosols, and thermal radiation from the warm atmosphere. Although there has been extensive work in developing models for $L_{SKY}$, local changes in atmospheric particulates and water vapor content can greatly affect model accuracy. In addition, a number of molecular species ($\text{H}_2\text{O}$, $\text{CO}_2$, $\text{CO}$, $\text{N}_2\text{O}$, $\text{O}_3$, and $\text{CH}_4$) have absorption bands in the infrared, which affect the incident solar radiation [10, §3.5.2]. The thermal contribution is most important at long wavelengths, and in this work we approximated $L_{SKY}$ by a blackbody radiator at the local air temperature.

C. Surface emission

Thermal emission from the soil surface depends on the surface temperature and emissivity. The surface temperature is obtained using the aforementioned thermal model. The spectral radiance of the soil (a graybody emitter) is given by the product of the surface emissivity $\mathcal{E}$ and the blackbody spectral radiance $L_{BB}(\lambda, T)$ described by Planck’s radiation law

$$L_{BB}(\lambda, T) = \frac{2c^2h}{\lambda^5} \frac{1}{e^{hv/kT} - 1} \quad [\text{W m}^{-2}\text{sr}^{-1}\text{μm}^{-1}],$$

(2)

where $h = 6.63 \times 10^{-34} \ \text{[J s]}$ is Planck’s constant, $\nu$ [Hz] is the frequency of the optical radiation, $\lambda$ [m] is the wavelength of that radiation, $k = 1.38 \times 10^{-23} \ \text{[J K}^{-1}]$ is Boltzmann’s constant, $c = 3 \times 10^8 \ \text{[m s}^{-1}]$ is the speed of light and $T$ [K] is the temperature.

The radiation diffusely emitted from a point $\mathbf{r}$ on the soil surface at temperature $T(\mathbf{r})$ can be written as the product

$$L_{surf}(\lambda, \mathbf{r}) = \mathcal{E}(\lambda, \mathbf{r})L_{BB}(\lambda, T(\mathbf{r})), \quad (3)$$

where $\mathcal{E}(\lambda, \mathbf{r})$ is the spectral directional emissivity. In Eq. (3) polarization effects, which are often directional and may be significant, have been ignored.

From the above expressions it is clear that emissivity has a direct effect on the thermal signature. In addition, grass and other forms of ground cover have a strong effect on the heat flow process and on the reflection and radiation of thermal energy. The emissivity of natural materials has been studied by Salisbury and D’Aria [11, 12]. In those works the
emissivity of soils, rocks and vegetation was described for both the 3-5 μm and 8-14 μm bands. The spectral response of these materials is complicated, but in general over the 3-5 μm band rocks and soils exhibit reflectance values of 5% to 30%, while vegetation has reflectance values of 2% to 15%. For the 8-14 μm band they found rock reflectance values of 1% to 10%. Vegetation reflectance values were found to have approximately the same range. The emissivity of these materials can be obtained from the reflectivity values by using Kirchoff’s law for an opaque body, \( R = 1 - \varepsilon \).

D. IR image formation

Equation (1) permits us to calculate the power incident on an IR detector surface \( D \) from the radiating soil surface \( S \). The power incident on the detector can be found by

\[
\Phi = \int_{\lambda_1}^{\lambda_2} d\lambda \int_{D} dD \int_{S} dS L_{\text{rec}}(\lambda, r) \frac{\cos \theta_1 \cos \theta_2}{R^2},
\]

where \( R \) is the distance between a point \( r \) on surface \( S \) and a point on the detector \( D \); \( \cos \theta_1 \) and \( \cos \theta_2 \) are projections of the normal vectors for surfaces \( D \) and \( S \), respectively, in the direction of the radiation; and the spectral band of interest is \( \lambda_1 \) to \( \lambda_2 \). In Eq. (4) the detector area is typically small, and the flux incident on each detector pixel is essentially constant. As a result, integration over the detector area is reduced to the product of the detector area and the flux falling on it.

The integration over the spectral band of interest \([\lambda_1, \lambda_2]\) is one-dimensional and presents no challenges for a narrow-band sensor. This integral is evaluated using a Gaussian quadrature rule. For a wider spectral domain with molecular absorption bands, evaluation of this integral is more challenging due to possible rapid variations in the integrand. To avoid possible numerical inaccuracy for larger spectral domains, we used adaptive Gaussian quadrature.

In terms of the computational time and memory requirements, the most challenging aspect of Eq. (4) is evaluation of the integral over the surface \( S \), which is the area of the rough surface seen by an individual image pixel. The projected surface area can be large for some combinations of camera height, location, and observation angle. In addition, the surface may be self shadowing. Two types of shadowing are taken into account in the radiometric model, and these are illustrated in Fig. 4. Some parts of the soil surface can
be invisible due to blocking as illustrated in Fig. 4 (a). To permit a general study of rough surfaces our radiometric model has been designed to deal with this form of shadowing, but practical sensor systems are often constrained to avoid these conditions, since they can lead to missed detections. Solar heating of the soil surface is also affected by shadowing as shown in Fig. 4 (b), and our model is also capable of handling this effect.

Integration over the projected surface areas is done using numerical quadrature techniques and is illustrated in Fig. 5 (a). As noted above, the soil surface is described by triangular facets with varying normal vectors. Every image pixel is divided into two triangles, and the integration domains comprise the projection of these triangles (or abscissas for numerical integration) onto the rough surfaces. The details of the selection of the integration abscissas and the integration rule are discussed below. The major difficulty at this point is the projection of the abscissas onto the surface facets. The challenge in this process is twofold: (1) deciding which surface facets contain the projections of the abscissas (shown Fig. 5 (a)), and (2) determining which of these facets will contribute to the integral at the specified integration point (shown in Fig. 5 (b)). This is a computationally challenging process due to the large number of facets and abscissas. For example, the relatively modest numerical simulations presented below in Sect. IV involve $48 \times 48 \times 2 = 4608$ surface triangles and $120 \times 160 \times 6 = 57600$ abscissa values. Visible surface determination is a computationally expensive process for this large number of points. Techniques offered by computer graphics are essential for computational efficiency. Specifically, a z-buffer algorithm [13] is utilized to determine the facet associated with an integration point. Once the projection of the integration point over a facet is determined, evaluation of the integrand at that integration point is required. The physical temperature, emissivity and surface normal direction are known at the integration points and, therefore, the integrand in Eq. (4) can be obtained with the aid of Eq. (1).

The accuracy of the integration over these triangular domains affects the fidelity of the simulation, and a number of tests were done to verify this accuracy. Different adaptive Gaussian quadrature rules were used over a simplex coordinate system. For our application the number of surface facets is smaller than the number of image pixels, which implies that a facet is in the field of view of several pixels. Furthermore, the functional variations
over these facets are smooth. Ultimately, we concluded that a non-adaptive three point quadrature rule produced acceptable results.

IV. Results

The thermal and radiometric models described above were used to simulate the temporal and spatial signatures of mines buried under smooth and rough surfaces. In all simulations a steady wind speed of $W(t) = 2 \text{ m s}^{-1}$ and an average air temperature of $T_{\text{air}} = 289 \text{ [K]}$ were used. The thermal diffusivity ($\kappa$) and conductivity ($\kappa$) of soil were taken to be $5.0 \times 10^{-7} \text{ [m}^2 \text{ s}^{-1}]$ and $2.6 \text{ [W m}^{-1} \text{ K}^{-1}]$, respectively. The mine was modeled as a homogeneous cylinder of TNT, for which we used $\kappa = 9.25 \times 10^{-8} \text{ [m}^2 \text{ s}^{-1}]$ and $\kappa = 0.234 \text{ [W m}^{-1} \text{ K}^{-1}]$. Mine dimensions vary significantly. As a simple but representative target, we selected a simulat anti-tank mine [14] developed by the US Army. The simulat mine has a diameter of 25 cm, a height of 8.33 cm, and was buried 6.64 cm

The radiometric model requires as input the triangular rough surface representation and the output of the thermal model. Using these data and the geometry given in Fig. 6, we constructed a virtual IR camera, the specification of which are given in Table I. The IR camera is aimed at point O (see Fig. 6), which is also the global coordinate origin for both the thermal and radiometric models. To cover the surface above the mine with sufficient resolution, an appropriate camera location and height must be identified. For this work we selected a camera height of 5.7 meters, and a horizontal standoff (camera center to point O) of 1 meter. The resulting ground-projected field of view encompasses most of the computational volume.

| Table I |
|-----------------|-----------------|
| **Spectral range** | **MWIR (4.4-5 \mu m)** |
| Array size | 160 (h) by 120 (v) pixels |
| FOV | $9.1^\circ$ (h) by $6.8^\circ$ (v) |
| IFOV | 1 mrad |
A. Mines under smooth surfaces

Figure 7 shows the simulation results for the surrogate mine buried under a smooth surface. The results are presented as a sequence of images evaluated at three hour time increments starting from sunrise. These results show phenomena identified previously, namely, the so-called thermal “cross-over” times at 11 AM and 9 PM. The IR signature of the land mine is clearly seen. Clutter-like variations, which are ubiquitous in experimental studies do not appear in the simulations.

B. Random rough surface modeling using experimental data

Rough surfaces were constructed by specifying random elevations for points in a rectilinear grid defined by the top surface of our FEM computational volume. The surface was then represented by triangles fitted to the grid points as shown in Fig. 1. The same representation was used by both the thermal and radiometric models.

To generate a random rough surface we require a description of the surface height statistics. In this work we used experimental data acquired by Salvati et al. [15] in support of a satellite remote sensing study. Those authors used a microtopographic laser scanner to measure surface heights on a grid of spacing 0.15 cm. The region sampled in their work was formerly cultivated farmland, which contained pronounced furrows. To simulate uncultivated soil we used data in the “down-furrow” direction and extended it isotropically. We approximated the resulting surface height spectrum using the following analytical expression

\[ W(k_x, k_y) = \exp \left( -L_1(k_x^2 + k_y^2)^{1/2} - L_2(k_x^2 + k_y^2)^{1/4} \right) \]  

where \( k_x \) and \( k_y \) are spectral frequencies in the \( \hat{x} \) and \( \hat{y} \) directions, respectively, and we estimated \( L_1 = 0.025 \) and \( L_2 = 0.25 \) from the data. The experimental and theoretical surface height spectra are plotted in Fig. 8. In addition, we compared the histogram of the data with a Gaussian distribution using the Kolmogorov-Smirnov (KS) test. The KS levels of significance deviate from unity by less than \( 4 \times 10^{-3} \), which strongly imply a Gaussian distribution.

The problem of generating a rough surface with a zero-mean, Gaussian distributed, height profile \( z = f(x, y) \) can be addressed by using the surface height spectrum \( W(k_x, k_y) \)
given by Eq. (5). Each spectral component is multiplied by a complex random number of unit magnitude and uniformly distributed phase $\psi_{m,n}$. We form the quantity

$$
P(m, n) = e^{+j\psi_{m,n}} \frac{2\pi N^2}{L} \sqrt{W \left( \frac{2m\pi}{LN}, \frac{2n\pi}{LN} \right)},
$$

where $N^2$ is the number of points in the discretization of the surface profile and $L$ is the edge-length of the surface. An example random surface generated in this manner is shown in Fig. 9.

Figure 10 shows the temporal evolution of a mine signature for the rough surface plotted in Fig. 9. Again, the results are presented as a sequence of images evaluated at three hour time increments starting from sunrise. In these figures it is harder to identify the mine signature, because the circular shape is lost. In addition, the imagery shows significant clutter, which could easily be mis-detected.

C. Random surface emissivity modeling

As noted in Sect. III-C, the radiation emitted from a surface is a function of surface emissivity. In this section we investigate the effects of a random surface emissivity profile. Using studies by Salisbury and D’Aria [11, 12] as a guide, we assumed soil emissivity values ranging from 0.8 to 0.9. To define the spatial distribution of the emissivity, we assumed a Gaussian distribution and a Gaussian spectrum given by

$$
W(k_x, k_y) = \frac{L_x L_y e_s^2}{4\pi} \exp \left( -\frac{L_x^2 k_x^2}{4} - \frac{L_y^2 k_y^2}{4} \right),
$$

where $L_x$ and $L_y$ are correlation lengths in the $x$ and $y$ directions respectively, and $e_s$ is the surface rms emissivity. In what follows we assume an isotropic surface with $L_x = L_y = L$. Equation (7) is used with Eq. (6) to obtain a realization of the surface emissivity. The resulting values are scaled to the range $[0.8, 0.9]$ to obtain the desired distribution. In Fig. 11 we have plotted an emissivity realization with correlation length $L = 5$ cm. Figure 12 shows the temporal evolution of the IR mine signatures for this emissivity. The emissivity variations break up the mine signature and the imagery shows significant clutter.
D. Model Validation

Efforts have been made to validate the combined thermal-radiometric model using experimental data.\textsuperscript{2} We used 8-12 $\mu$m calibrated images of AT mines acquired by TRW at times near 10:00 AM and 12:00 PM. The images were acquired at the US Army Fort A.P. Hill, Site 71A mine lanes #13 (dirt) and #14 (gravel). Collateral information was collected including soil temperature at multiple depths (0.5", 2", 4", 8"), wind speed and direction, soil moisture content (one depth), air temperature, barometric pressure, and down-welling and up-welling radiance in the 0.3-3 $\mu$m and 3-50 $\mu$m spectral bands.

To predict the measured data, it was necessary to make assumptions about several unknown environmental parameters. Specifically, we assumed soil thermal conductivity=1.8 [W/mK] and diffusivity=10\textsuperscript{-6} [m\textsuperscript{2}/s] for the given moisture content in a clay-loam soil. The mine (an “EM-12” mine surrogate) is known to have a 30 cm diameter and 5.2 cm height. The mine’s internal contents are not known, and because it is part of an active test site it was not possible to excavate the mine and examine it (to avoid disturbing the target for subsequent tests). Collateral information suggested a filling of styrofoam pellets and carnuba wax with an overlying void, which we modeled as a good thermal insulator. The thermal model’s FEM mesh was constructed of pentahedral elements with cell dimensions of 1.27 cm (height) by 2.56 cm (base). Other environmental parameters were derived from the available data and models. A surface emissivity of 0.98 was assumed. MODTRAN was used to estimate the incident radiance as a function of time, and it was found to replicate measured values to an accuracy of 10%.

The measured data appear in Fig. 13 (a). To reduce small-scale image clutter related to surface roughness and emissivity variations we applied a low-pass filter to the original data, which produced the imagery shown in Fig. 13 (b). The model results appear in Fig. 13 (c), the shape of which is seen to compare well with Fig. 13 (b). A one-dimensional cut through the data is shown in Fig. 13 (d), which helps to quantify the agreement. We see that the signature shape and temperature contrast are fairly well predicted, but the model temperature is approximately 2K below the measured data. There are several possible sources for this error including incorrect parameter estimates and our use of periodic

\textsuperscript{2}Validation of the thermal model alone using independent models has been discussed in a separate work [16].
thermal boundary conditions in time. Warmer conditions the previous night can produce an offset that is not easily addressed without prior temperature data. The agreement in Fig. 13 is encouraging, but additional work in validation is clearly called for.

V. CONCLUSIONS

A radiometric model has been presented for the spatial and spectral IR signatures of buried land mines. Atmospheric effects and the spectral content of natural sources are taken into account via the MODTRAN model. Both the thermal and radiometric models used in this study incorporate a rough surface for the soil-air interface, which has implications for both thermal heating and for reflected radiometric components. The temperature distribution computed using the thermal model is combined with surface-reflected radiometric components to produce the image seen at an IR sensor. Simulations of mines under rough surfaces were performed, and it was found that surface roughness can add appreciable clutter. In addition, random variations in the surface emissivity profile were found to be another potential source of clutter. An effort was made to validate the model using experimental data. It was found that the signature shape and temperature contrast are fairly well predicted.

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Fig. 1. Sample spatial discretization of the computational domain. The volume is subdivided by pentahedral elements resulting in a triangular mesh for the soil surface, which is emphasized with thicker lines.
Fig. 2. Contributors to a thermal image of the ground include direct sunlight, aerosol-scattered sunlight, thermal emissions from the air reflected by the ground, and thermal emissions from the soil.
Fig. 3. Predicted spectral radiance at Columbus, OH on April 3. (a) Solar spectral radiance with no atmospheric effects. (b) Prediction by MODTRAN at 10 AM. (c) 12 PM (d) 2 PM (d) 4 PM (d) 6 PM
Fig. 4. (a) Surface roughness can produce obscuration. (b) Heating of the soil surface is affected by shadowing.
Fig. 5. (a) Projection of the integration abscissas onto the facets forming the rough surface. (b) Visible surface determination is required because of shadowing.
Fig. 6. Sketch of the region of interest including the IR camera. Point O is both the center of the field of view and the origin of coordinates. The image plane, the ground transformed image, the surface boundaries of the computational volume, and the global axis are illustrated.
Fig. 7. Simulation of the IR signature of the SIM-25 mine buried 6.66 cm under a smooth soil surface for a sensor located 5.7 m above and 1 m to the right of the mine. The radiometric model is used to predict the response at different times of the day: (a) At dawn. (b) 3 hours after sunrise. (c) At noon. (d) 3 hours after noon. (e) At sunset. (f) 3 hours after sunset.
Fig. 8. Comparison of the experimental and model PSDs.
Fig. 9. An example of a rough surface realized using a Gaussian spectrum with correlation length $L = 20$ cm.
Fig. 10. Simulation of the IR signature of the SIM-25 mine buried 6.66 cm under a rough soil surface with peak to peak height variations of 5 cm. The radiometric model is used to predict the response at different times of the day: (a) At dawn. (b) 3 hours after sunrise. (c) At noon. (d) 3 hours after noon. (e) At sunset. (f) 3 hours after sunset.
Fig. 11. An example surface emissivity realized using a Gaussian spectrum with correlation length $L = 5$ cm.
Fig. 12. Simulation of the IR camera response of the SIM-25 mine buried 6.66 cm under a smooth soil surface with a Gaussian surface emissivity profile. The radiometric model is used to predict the IR camera response at different times of the day (a) At dawn. (b) 3 hours after sunrise. (c) At noon. (d) 3 hours after noon. (e) At sunset. (f) 3 hours after sunset.
Fig. 13. (a) Raw experimental data. (b) Measured data after low-pass filtering to remove surface clutter. (c) Model prediction. (d) Comparison of model and experiment.