

radiation of its own. According to the Stefan-Boltzmann law, the radiated power is proportional to the fourth power of the body's absolute temperature and to its emissivity. The sensor receives the emitted and reflected components of the radiation. The reflected component is negligible compared to the emitted component for two reasons. First, infrared radiation reflectivity values are low for most materials occurring in natural scenes such as vegetation, sand, soil, rocks, and painted metal and second because the sun's surface temperature is approximately 5672K, and according to Planck's law very little of its emitted radiation lies in the commonly used infrared wavelengths (8 to 12 μm), whereas objects in natural scenes with average temperatures of 250 to 350K emit primarily at these wavelengths.

In FIG. 1, the surface temperature of the body is represented as T_s , its interior temperature as T_o , T_{amb} is the ambient temperature of the atmosphere, I_{cnv} is the heat convected from the surface to the air, I_{rad} is the emitted radiation, I_{cnd} is the heat conducted from the object surface to its interior, and I_{abs} is the total heat absorbed by the surface. At any point in time, a balance exists among the radiation components flowing into the object surface and those flowing out. This can be written as

$$I_{abs} = I_{cnv} + I_{rad} + I_{cnd} \quad (1)$$

The various radiation components can be computed from the following relations:

$$I_{abs} = \eta f(t) \quad (2)$$

where η is the absorptivity of the surface material and $f(t)$ is the time dependent solar radiation incident on the object surface.

$$I_{cnv} = h(T_s - T_{amb}) \quad (3)$$

where h is the average convection heat transfer coefficient, and depends on the properties of the surrounding air (e.g., air velocity, viscosity, temperature etc.), and also to some extent on the geometry of the surface. The effect of the surface geometry can be ignored for typical wind velocities up to 15 mph as the convection tends to be laminar and convection relations developed for external flow over flat plates can be used. For higher wind velocities the convection becomes turbulent and object geometry will have an appreciable effect on it. For the present we ignore such situations. Numerous empirical techniques exist for computing h and some of them are given by F. P. Incropera and D. P. DeWitt in their book "Introduction to Heat Transfer" published by John Wiley & Sons, 1985.

$$I_{rad} = \sigma \epsilon (T_s^4 - T_{amb}^4) \quad (4)$$

where σ is the Stefan-Boltzmann constant ($5.670 \times 10^{-8} \text{ W/m}^2\text{K}^4$), ϵ is the emissivity of the object. Most objects in natural scenes have emissivity values close to 0.9, so a constant value of 0.9 is assumed for all bodies.

$$I_{cnd} = \xi (T_s - T_o) \quad (5)$$

where ξ is the element conductivity. Note that the values of η and ξ vary from surface to surface and are

indicative of the surface material. In terms of these relations (2)–(5), equation (1) above can be rewritten as:

$$\eta f(t) = h(T_s - T_{amb}) + \sigma \epsilon (T_s^4 - T_{amb}^4) + \xi (T_s - T_o) \quad (6)$$

The above equation is the heat balance equation. This equation is valid on a pixel to pixel basis for a given infrared image. In this equation $f(t)$ is assumed known, T_{amb} can be measured, and while T_o need not be constant for the entire region being imaged, it is assumed so as a first approximation. The computation of h has already been discussed above, and we use the following method to compute T_s from the grey-scale infrared image. This method is given in detail by N. Nandhakumar and J. K. Aggarwal in their paper entitled "Integrated Analysis of Thermal and Visual Images for Scene Interpretation" published in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, corresponding to a surface temperature T_s then

$$K_a G_i + K_b = \int_{\lambda_1}^{\lambda_2} \frac{\epsilon C_1 \tau_{\lambda R}}{\lambda^5 (\exp(C_2/\lambda T_s) - 1)} d\lambda \quad (7)$$

In this equation K_a and K_b are calibration constants of the imaging system. The quantity on the right hand side corresponds to radiation in the infrared band received by the sensor. (λ_1, λ_2) is the range of infrared wave lengths being imaged. Typically $\lambda_1 = 8 \mu\text{m}$ and $\lambda_2 = 12 \mu\text{m}$. C_1 and C_2 are universal constants. $C_1 = 3.742 \times 10^8 \text{ W}\cdot\mu\text{m}/\text{m}^2$ and $C_2 = 1.439 \times 10^4 \mu\text{m}\cdot\text{K}$. ϵ is the surface emissivity, assumed 0.9 as explained previously. $\tau_{\lambda R}$ is the spectral atmospheric transmission for range R , obtained from the standard LOWTRAN codes. K_a and K_b are obtained by imaging two bodies at different known temperatures. The corresponding grey scale values are measured and substituted along with T_s in the above equation to obtain two linear equations in the unknowns K_a and K_b which can then be solved for these parameters. It is then desired to compute T_s for any given G_i . Current techniques do this by precomputing the integral in the above equation for various values of T_s and creating a table of these values. The observed grey scale is used to compute the left side of the above equation and this value is then matched to the table to get the corresponding T_s .

The unknowns in the heat balance equation are η and ξ . These values will change from pixel to pixel and because of the continuity of the physical surfaces being imaged, the values at any given pixel will be related to those at the neighboring pixels. This equation has to be solved for η and ξ on a pixel to pixel basis. This is a linear equation in the unknowns, and as there are two unknowns but only one equation, it is an ill-posed problem. Solution methodologies for ill-posed problems are an extensive field in mathematics, and many well-known techniques exist.

One powerful technique is Bayesian estimation using Markov random fields (MRFs). MRFs have been used by various researchers in computer vision and image processing, such as by S. Geman and D. Geman; reported in "Stochastic Relaxation, Gibbs Distribution, and the Bayesian Restoration of Images," published by *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 6(6):721–741, Nov. 1984 and as by J. Marroquin, S. Mitter, and T. Poggio reported in "Probabilistic Solution of Ill-Posed Problems in Computational Vi-