Material Classification with Thermal Imagery

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Material classification is an important area of research in computer vision. Typical algorithms use color and texture information for classification[2]. Thermal (long-wave infrared) imagery has the benefit of relative invariance to color changes, invariance to lighting conditions, and can even work in the dark. However, it has not been heavily studied for material classification. [5] uses near infrared (NIR) to get a more intrinsic image of the material sample. [4] uses mid wave infrared for paper and board identification for food packaging. [3] measures thermal conductivity of materials using tactile feedback; a robot touches the material with a probe. None of these works user thermal (long-wave infrared) imagery.

We develop a set of features that describe water permeation and heating/cooling properties, which are easy to see in thermal imagery but not in traditional color imagery. An overview of our methods can be seen in Figure 1. There are a few interesting features that can be obtained for water permeation such as the rate of permeation of the water into the material and the shape characteristics of the permeation. We generalize these features by creating a 3D model which we call the CHAMP (CHAracteristic Model of Permeation). The CHAMP can be understood by visualizing each image in a video sequence as a 2D slice along the Z dimension. It implicitly contains the shape of the water permeation as well as the growth rate (i.e. curvature of the model).

Once the models are created, a metric to compare the models is needed. We chose to compute a Fast Fourier Transform of a modified binned spherical mapping of the CHAMP. This is a robust method since it is invariant to rotations and translations between CHAMPs and is fast to compute.

Before performing the spherical mapping, we first center the CHAMP around its centroid. Next, we map (X,Y,Z) in the Cartesian coordinate system to (r,θ,ϕ) in the spherical coordinate system using simple trigonometric equations. These spherical points are binned into a 2D histogram image. The intensity values of the histogram image are the r values multiplied by $cos(\phi_k)$, the rows are varying θ, and the columns are varying ϕ. This is performed by

$$\begin{aligned} SPH(x,y) &= cos(\phi_k) * avg(r_k) \\ &\{k \mid \theta_k \pm \varepsilon = x * bin_x - \pi, \\ &\phi_k \pm \varepsilon = y * bin_y - \frac{\pi}{4}\}, \end{aligned} \tag{1}$$

where bin_x and bin_y are the desired bin size. Each row corresponds to a slice of the model, and the values are the distances from the centroid of that slice to the edge of the model.

Next, we compute the FFT of these 2D histogram images and shift the zero-frequency component to the center. Since the only misalignment of the spherical maps will be in the horizontal direction, we can ignore the phase and take the amplitude of the FFT image. This allows our FFT images to be aligned even if the CHAMPs are misaligned due to rotations and translations.

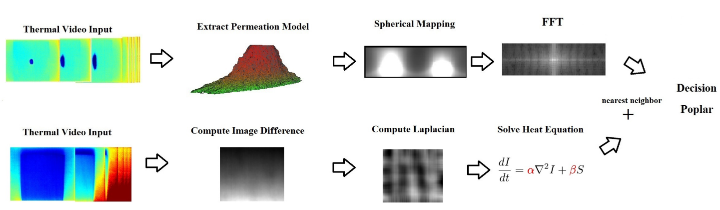

Figure 1: The proposed method consists of two types of features – water permeation and a heating/cooling cycle.

For heating/cooling, we describe two features. Our first attempt of feature extraction of heating and cooling is quite simple. For each image in an infrared video stream, we sample five patches. For each patch, the mean temperature over the patch is plotted over time to give a temperature curve that should, ideally, be unique for each material. Patches were chosen over using all pixels to smooth over noise and to speed up the processing time. To account for change in room temperature over the course of a day, we align the starting temperatures of each curve when comparing across materials, i.e. for materials x and y perform $T'_{xk}(t) = T_{xk}(t) + [T_{yk}(1) - T_{xk}(1)]$. Here $T_{xk}(t)$ is the temperature at time t for material x at patch k. Euclidean distance is used as a metric for comparison.

The second feature solves the heat equation [1] for two parameters α and β. The heat equation [1] is a parabolic partial differential equation that describes the distribution of heat over time. We augment the standard heat equation to more closely describe our physical setup by adding a second term as in

$$\frac{dI}{dt} = \alpha\nabla^2 I + \beta S(t), \tag{2}$$

where α, β are unknown constants, and S is a function which describes how heat is applied. In our setup, a heat lamp was the source of heat in the scene, and its temperature changed over time. To calculate S, we sampled the temperature of the heat lamp over time using an infrared thermometer, and fit a piecewise polynomial to the sample temperatures. Once S is known, we can calculate α, β by setting up an overconstrained linear system and applying a Moore-Penrose pseudoinverse.

In our experiments we used a Xenics Gobi 640 GigE uncooled long wave infrared camera, which has a resolution of 640x480 and has a 50mC sensitivity at 30°C. The materials we used were broken up into 5 coarse classes: cloth, wood, paper, plastic foams, and metal. Each coarse class was further broken up into a total of 21 subclasses. For each type of material, we imaged 4 samples; this gives a total of 84 material samples. We tested a few variations including: "capping" the CHAMP, using aligned spherical maps without FFT, and using aligned spherical maps without the $cos(\phi)$ term in Eq. 1. Our results show up to 96% accuracy for the fine grain classification, and 100% when combining water permeation and heating/cooling features.

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This is an extended abstract. The full paper is available at the Computer Vision Foundation webpage.