

Thermal Spread Functions (TSF): Physics-guided Material Classification

Supplementary - CVPR 2023

1. Finite Difference Model - Performance

Figure 10 demonstrates the performance of our inverse Finite Difference algorithm for recovery of diffusivity k and absorption coefficient ϵ' . We show images at intermediate time-steps, one while the material gets heated (Figure 10(a)) and another image while it is cooling off after the source is turned off (Figure 10(b)). We also show our simulation setup in Fig. 11.

2. Advantages over spectral methods

For the PVC readings, we painted one of the faces with a highlighter (refer Figure 12(a)) and tried our approach and it still worked quite well (refer to Fig. 7(b) of the main paper, where the classification accuracy is 100% for PVC). This proves that small surface manipulations do not hinder our approach - unlike other spectral or RGB-image based methods.

3. Tuning the hyper-parameter of learning rate

Despite having automated everything else in our code, there is still one hyper-parameter that needs tuning in our setup - the learning rate for the optimization. We need to adjust the learning rate so that the optimization - (a) does not get stuck in a local minima and (b) does not wildly oscillate and hence not converge. Currently we do this manually by looking at the loss and diffusivity convergence curves but this process can be optimized as shown by previous work [1]

4. Special case - metals

We tried our approach on metals but it didn't work right off the bat because of two reasons - (1) The reflectivity of metals is too high and their emissivity is quite low. This means, it reflects most of the light we shine on it and whatever small fraction is absorbed and leads to a minor temperature change, is not visible because only a fraction of that reaches camera (because of low emissivity) (2) The diffusivity of metals is very high. Combined with its high reflectivity and low emissivity, we need a much higher power laser compared to the one we use currently (60mW).

Workaround: We tested another method to still get some classification means for metals for the low powered laser. We pasted a tape on top of the metal cubes. This gives us the advantage of low reflectivity and higher emissivity. Thus, we might get absorption properties of the tape but the diffusivity for the metal can be obtained in this method. Please find the setup in Figure 12(b). The confusion matrix obtained upon classification for these metal cubes is shown in Figure 14.

5. Two layers - going under the surface

We performed simulations to test out our hypothesis of using this approach to find properties of under-the-surface materials. We created a heat diffusion simulation using our forward FD model, where the surface layer with a thickness of 0.5mm, has a diffusivity of $1^{-7} \epsilon' m^2/s$. The layer below it has a diffusivity of $2^{-7} \epsilon' m^2/s$. We assume the thickness of top layer as a known parameter for this optimization. After running our optimization algorithm for recovering 2 layer properties, we got a diffusivity for top layer as $0.995^{-7} \epsilon' m^2/s$ and a value of $2.002^{-7} \epsilon' m^2/s$ for the bottom layer (refer Figure 15). These values match very closely with the original values which makes it a good direction to work on in the future.

6. Varying capture time t_{ON}

Apart from the results shown in the paper, we also tried various smaller capture times for our setup. The TSFs are similar for the materials for all the t_{ON} 's (refer Fig. 13). We found that our approach resulted in similar results for a total capture duration of 20s or higher. While this duration can be further reduced with implicit approaches such as PINN, the physical process of heat dissipation requires a minimum duration, which often tends to be several tens of seconds.

References

- [1] Leslie N Smith. Cyclical learning rates for training neural networks. In *2017 IEEE winter conference on applications of computer vision (WACV)*, pages 464–472. IEEE, 2017. 1

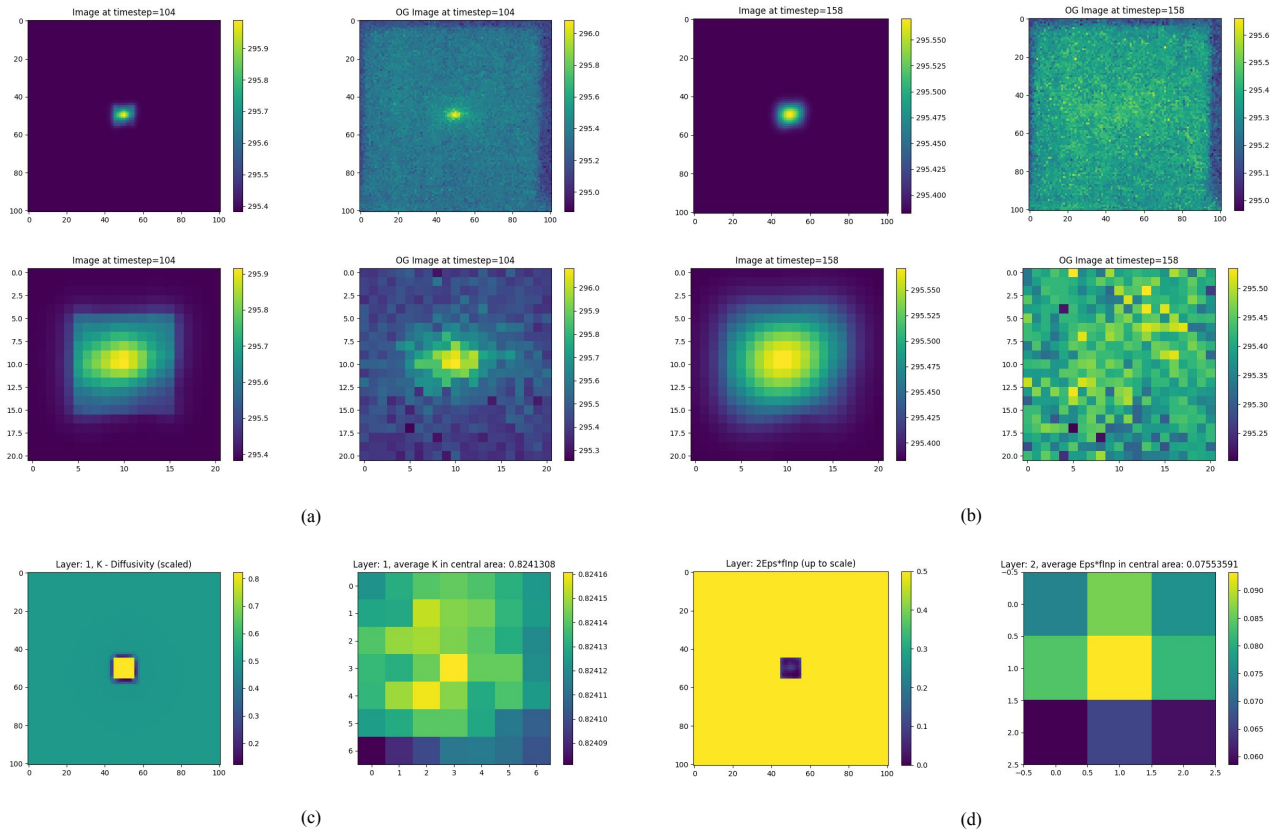


Figure 10. **Finite Difference Performance.** (a) **While the source is still on:** (Left) Images obtained at time-step = 104, from FD method after optimization (Bottom row is the zoomed-in version of top row) (Right) Original images captured from the thermal camera. (b) **After source is switched off:** Similar comparison of FD result and original captured image at time-step = 158. (c) The resultant diffusivity (k) image obtained after the optimization is complete, (left) original image (right) zoomed-in version (d) The resultant absorption coefficient (ϵ') image (left) original image (right) zoomed-in version. The results displayed are for Oakwood, average MSE error over the set of images is 8.68^{-3} .

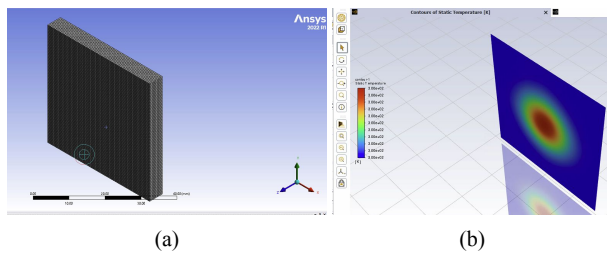


Figure 11. **Ansys Fluent FEM Analysis software.** (a) We give a custom heat injection on the surface of the material for few seconds and then turn it off. (b) We observe the surface temperature variation and do our analysis based on only surface temperatures which is what would be available to us during real measurements.

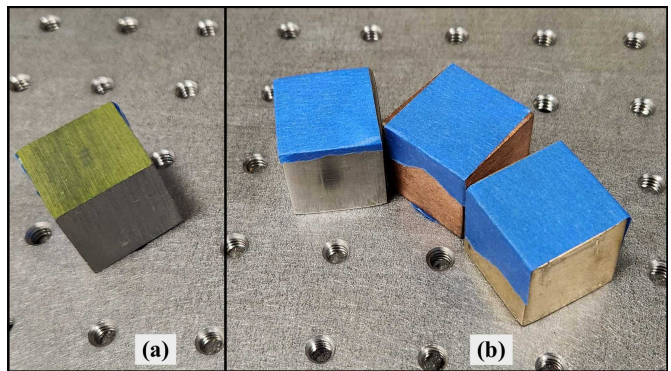


Figure 12. **Metals Taped.** (a) We painted a PVC block with a green highlighter and tried the same approach and our algorithm correctly classifies the material. (b) We pasted a Scotch blue paper-tape on top of the metals - (left-to-right) Stainless Steel, Copper and Brass.

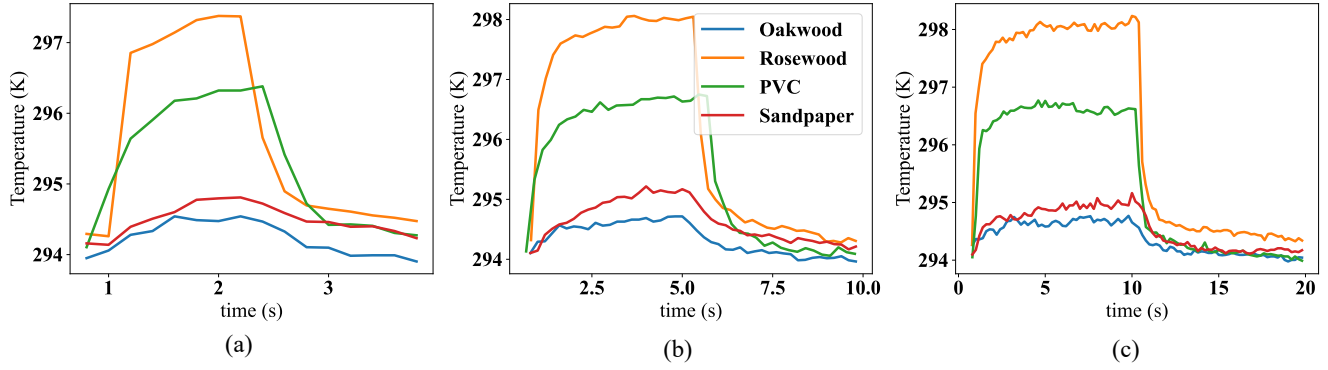


Figure 13. **TSFs for various scan durations.** TSFs plotted for Oakwood, Rosewood, PVC, and Sandpaper for time durations (a) 4s, (b) 10s, (c) 20s

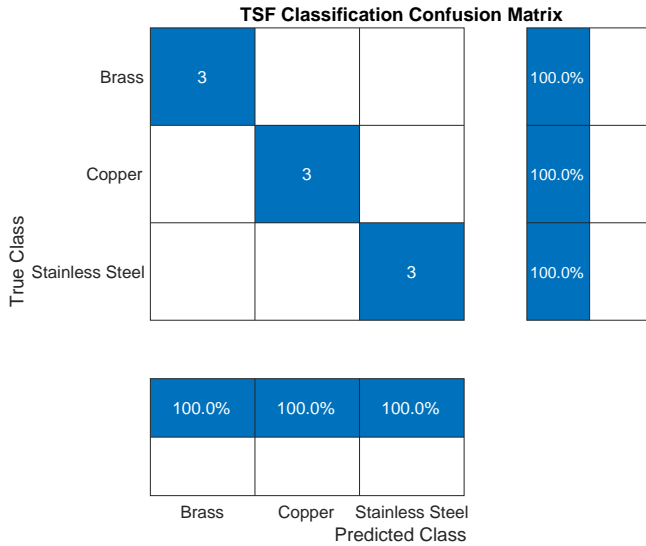


Figure 14. **Confusion Matrix for metals.** We perform leave-one-out validation to gauge the accuracy of our classification using TSF.

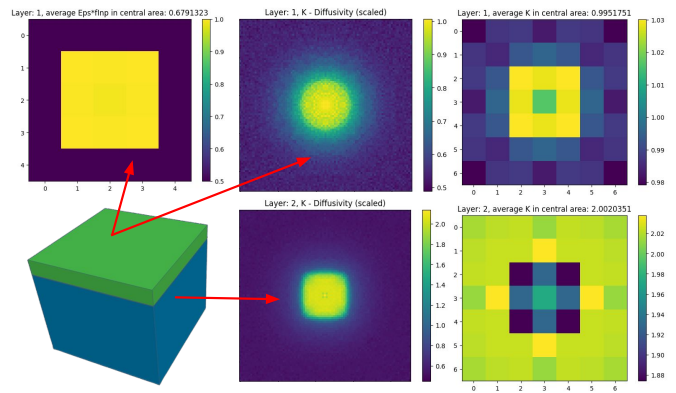


Figure 15. **Recovering properties of hidden material.** (Top) Recovered properties of the top layer - absorption coefficient ϵ' , thermal diffusivity k and its zoomed-in version. (Bottom) Two-layered material, and properties of the bottom layer - thermal diffusivity k and its zoomed-in version.