University of Information Technology

Final year project

An Overview of Material Classification

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1 Introduction

What is material classification?

The main goal is providing the detail of material information in an image.

In simple words, given an image I, the computer need to find out what material its surface is made of (such as metal, plastic, stone, brick, glass, wood, etc.).

Figure 1: Example for finding material of surface in a single image

In A higher level, the computer even need to know exactly what material class for every single pixel in the image.

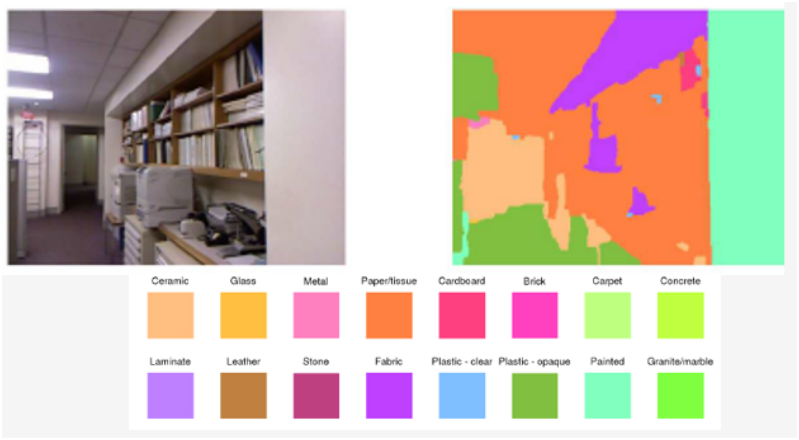

Figure 2: Example for finding material for every single pixel in an image

In this task, i will work on the simple problem (finding material of an image).

Why do we need material classification?

In recent years, material classification has become an active topic for researchers with the main goal is providing the detail of material information for a vareties applications such as Advanced Driver-Assistance Systems (ADAS) [1], robotic manipulation [2], robotic navigation [3], etc.

Figure 3: Bottles with similary shapes, are made of diffrenet materials which decides its physical properties, which could be extremely useful information in various situations.

Material of surfaces contribute valuable informations to understand the whole image. For example, Figure 3 shows that with infomation about material which thoses bottles make of, computer could sort those bottles by weights, make a decision to choose which one is good to hold hot water or even know that it would be a risk to allow people bring a glass bottle which could be used as a weapon into a meeting between head of states.

Challenges

In real world, materials have rich surface texture, geometry, lighting conditions, and clutter, which combine to make the problem more challenging.

Figure 4: Objects in both scene can be considered as "stone"

Figure 5: Objects with same texture and different material

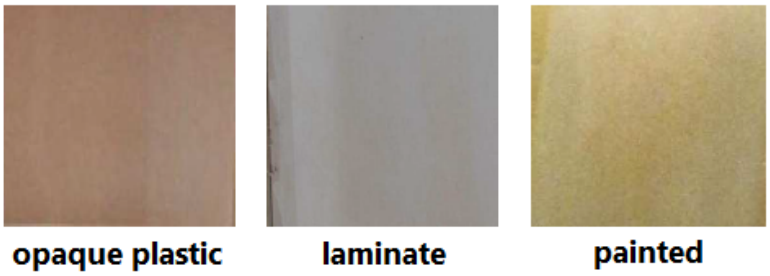

Figure 6: An example from Open-Surface dataset shows how this task challenging

2 Related Work

Like many other classification problems in Computer Vision, the solutions for this task focus on finding features to represent for the image from which images with different materials should have a long distance between their feature vectors, then apply learning algorithms to find a model classify them.

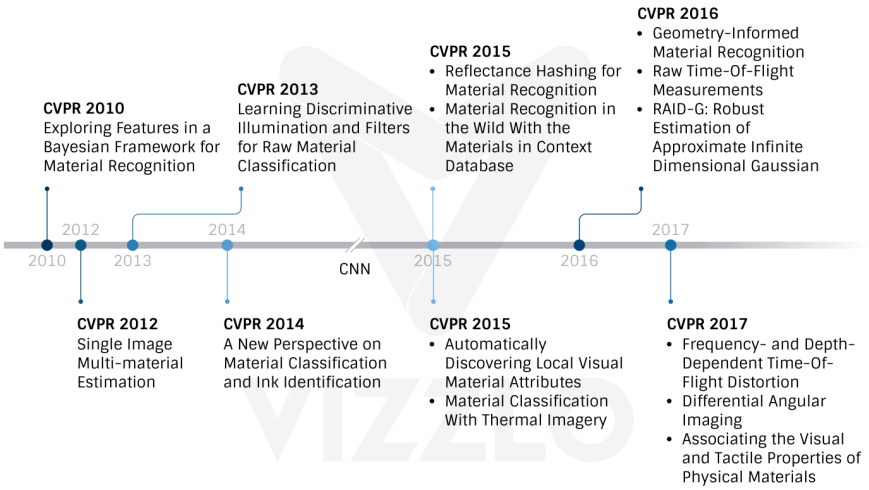

Figure 7: Related works in CVPR from 2010 to 2017, After CNN appears (2014 - 2015) material classification becomes more and more active with variants of papers published

3 Dataset

As a result of when CNN appears, a lot of dataset related to material also were published.

Name	Samples	Classes	Views	Illumination	In scene	Scene image	Camera parameters	Year
CUReT	61	61	205	205	No	No	No	1999
KTH-TIPS	11	11	27	3	No	No	No	2004
UBO2014	84	7	151	151	No	No	No	2014
Reflectance	190	19	3	3	No	No	Yes	2015
4D Light-field	1200	12	1	1	Yes	No	No	2016
NISAR	100	100	9	12	No	No	No	2016
GTOS	606	40	19	4	Yes	Yes	Yes	2016

Table 1: Some publicly available BRDF material datasets [4]. Note that the 4D Light-field dataset is captured by the Lytro Illum light field camera.

4 My current work

The paper I choose to work on

Name Differential Angular Imaging for Material Recognition (DAIN)

Dataset GTOS (Ground Terrain in Outdoor Scenes).

Authors Jia Xue, Hang Zhang, Kristin Dana, Ko Nishino from Computer Vision Lab, Rutgers University - New Jersey (USA).

Website http://eceweb1.rutgers.edu/vision/index.html

Why do I choose this paper?

1. Newest paper about material classification published in CVPR2017.
2. Work with a new dataset (GTOS - published 2016) large scale, high quality. Coming soon, GTIS (Ground Terrain in Indoor Scenes) more challenges.
3. Best result compare with the state of art algorithms on the same dataset.
4. The key idea of solution in this paper is not complex so I can moving on.
5. Published source code. You can download it here

Architecture	Accuracy
FV+CNN	75.4
FV-N+CNN+N(3D)	58.3
MVCNN	78.1
Multi-view DAIN (3D filter) pooling	81.4

Table 2: Comparison Multi-view DAIN with the state of art algorithms on GTOS dataset [4]

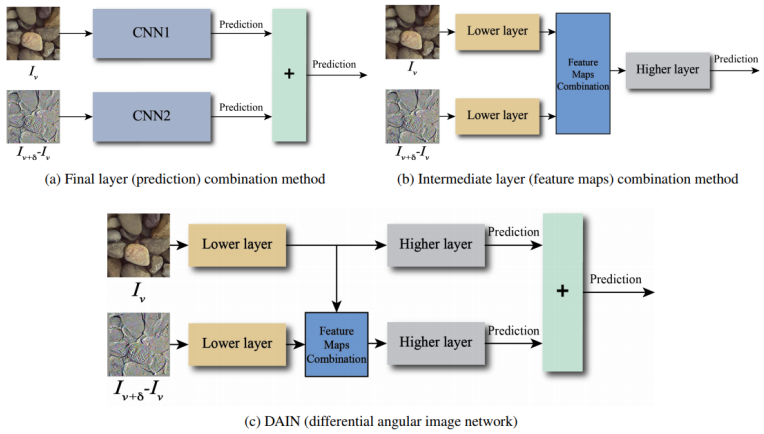

Figure 8: Basic idea of DAIN is combining the original image and addition information about angular [4]

My baseline result

Feature extraction I extract VGG16-fc2 feature with Keras framework (using Tensorflow as backend).

Training process Then, training with SVM (from scikit-learn python package) with my custom parameters.

Testing process Finally, testing on 5 different train-test splits (same as the original paper).

Train-test split	Accuracy
01	73.17
02	77.01
03	77.79
04	81.24
05	80.44
Average	77.93

Table 3: Baseline result with VGG-16(fc2) SVM result on GTOS

5 My future work

The DAIN paper gives a good result for lighting and shape variant challenges with additional information about angular of the image. They didn't consider about texture information so i will focus on combining texture, angular and the original image into one classifier. But firstly, i want to apply a little bit change to DAIN (i means i would use the same idea with angular information, just change the training process - see below).

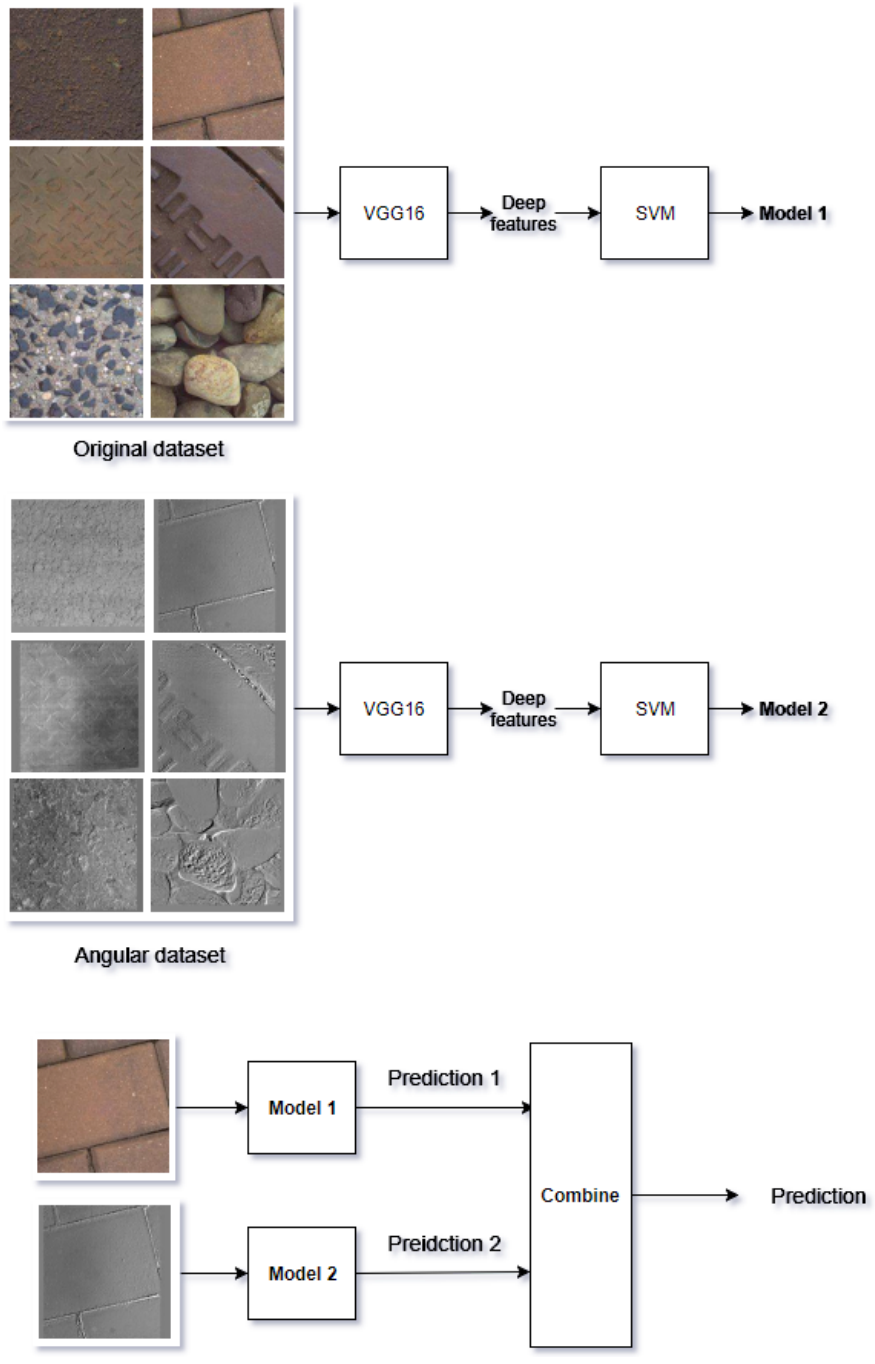

Figure 9: Prediction combined with SVM instead of combining final layer of CNN in DAIN

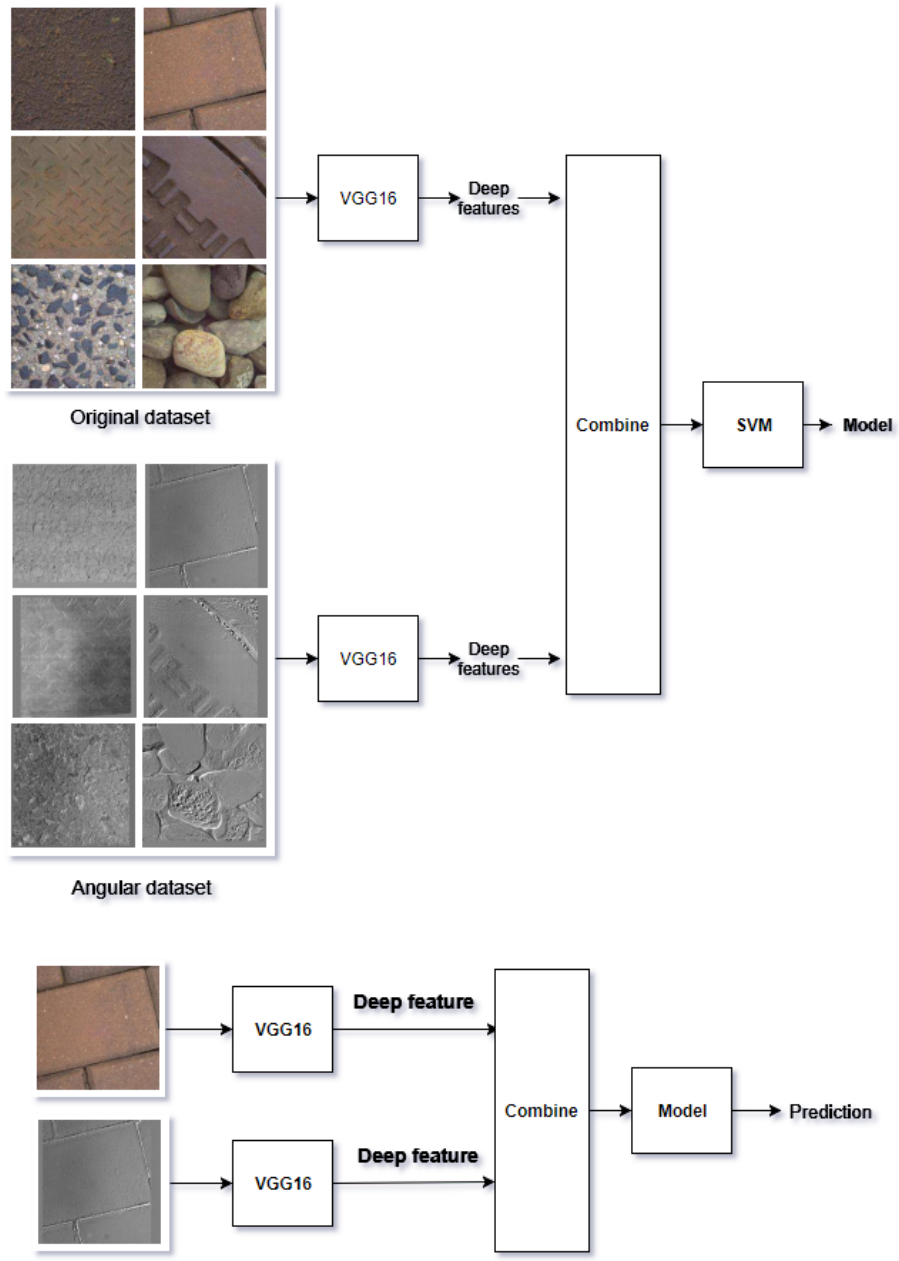

Figure 10: Feature combined with SVM instead of combining intermediate layer of CNN in DAIN

6 References

[1] *Nvidia, advanced driver assistance systems.* [Online]. Available: https://www.nvidia.com/en-us/self-driving-cars/adas/.

[2] M. W. Spong, S. Hutchinson, and M. Vidyasagar, *Robot modeling and control.* Wiley New York, 2006, vol. 3.

[3] J.-H. Kim, E. T. Matson, H. Myung, and P. Xu, *Robot intelligence technology and applications 2012: An edition of the presented papers from the 1st international conference on robot intelligence technology and applications*. Springer Science & Business Media, 2013, vol. 208.

[4] J. Xue, H. Zhang, K. Dana, and K. Nishino, "Differential angular imaging for material recognition", *ArXiv preprint arXiv:1612.02372*, 2016.

7 Appendices