Deep Feature and Handcrafted Feature:
A Combination for Material Classification

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Abstract—By somehow, we - human beings interact with the physical world every single second. It is a proof for our existence. Similarly, for computers to truly "exist" as humans, they also need to be able to communicate with this world. To make it come true, they will need to collect a lot of different information outside and really understand it. One of the most basic and essential information is material of the environmental surface. Because of this importance, the material classification problem for the purpose of extracting information about material as detail as possible has been interested and developed carefully over the years. In the real world, materials have rich surface textures, geometries, lighting conditions, and clutter, which combine to make the problem more challenging. In this paper, We propose an image-based classification method using deep feature from the original image and geometry information as handcrafted local features. With this combination, we demonstrate the effectiveness and extensible of our method through experiments on newest material datasets.

I. INTRODUCTION

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

Fig. 1: Bottles with similar shapes, are made of different materials which decides its physical properties, which could be extremely useful information in various situations.

Material of surfaces contributes valuable information for computer to understand the whole image and interact with the physical world. For example, Figure 1 shows that with information about material which those 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.

Fig. 2: Human can easily predict the material of similar texture surfaces by using some of their basic geometry informations (like shape) [4].

Early studies works on material classification are focused on using lab-based measurements to capture physical properties of object surface which are extremely helpful to predict the material. However, those method also limits their application due to the needed of special equipment. A different approach is image-based classification where surfaces are simply capture as single view images to train classifiers. In these methods, recognition is typically based more on context than physical properties of objects. Taking advantages of both approaches, in this paper, we suggest an image-based method with additional information about basic physical properties of object surface such as geometry and texture extracted as local features which similar to what human think when we try to predicting material of object from an image (see figure 2 and 3).

Fig. 3: While the main object in both scenes can be considered as "stone" because of its shape, we can also easily know which one is "real stone" based on its texture [5].

In summary, our contribution is proposing an effective method not only for classifying material from a single 2D-RGB image, but also for other classification task.

II. RELATED WORK

There are several approaches for material classification. Some of existing techniques based on physical properties of object (lab-based) such as elasticity [6], water permeation [7] or optic response [8] give a high performance on distinguishing different types of similar materials because of rich information they provide. However, It generally requires a lot of special equipments to building those types of systems and datasets. Additional, with different approaches following this techniques we also usually need collect a new specialized dataset depends on which type of physical properties we want to get (Ex. GelFabric [9] - released in 2016 for Visual Perception on Fabrics Studies with color deep images, GelSight videos, and human labeling of the properties; Ground Terrain in Outdoor Scenes (GTOS) [10] - 2016 for multi-view points information; Reflectance Disk Database [11] - 2015 for reflectance of surfaces). Therefore, methods in this group can archive state-of-the-art on a specific dataset and also can easily fail on another (or can not be used on another because of missing informations).

On the other hand, alternative image-based techniques typically only require a natural RGB image and therefore can be set up easily on any dataset. Basing on the visual appearance and often replying on object classification to predict material, the main problem of these methods is lacking information and easily fooled by similar visual appearance such as shape.

Recently, features learned from Deep Neural networks has proven its valuable in object recognition and also transformed to the material field including both material classification and material segmentation. Bell et al., achieved per-pixel material category labeling by using a state-of-the-art object recognition network [12]. We have also been motivated by the two-stream fusion network which achieves state-of-the-art on GTOS dataset 2017.

III. METHOD

As mentioned above, 2D-image base methods often replying on object classification to predict material and easy fooled when the objects have the same shape or texture but different material. We develop a method that combine deep features extracted from a CNN represent for current modern approach for object classification with handcrafted features includes edges and textures information to avoid miss classification samples have different material from similar objects. The main idea of our method is shown in figure 4.

We used the ImageNet pre-trained VGG-16 model as a deep feature extraction (from the "fc2" layer) and SVM for training classifier. The first input branch is original 2D-image, the second branch is edges image which is generated by using some common edges detector and the third branch is texture image which also generated by using texture filters.

In the first method, each branch will be trained particularly, then using three different classifiers to get probability predictions for each test sample. Finally, We combine the probability result from all branches with a simple averaging computation (see figure 5).
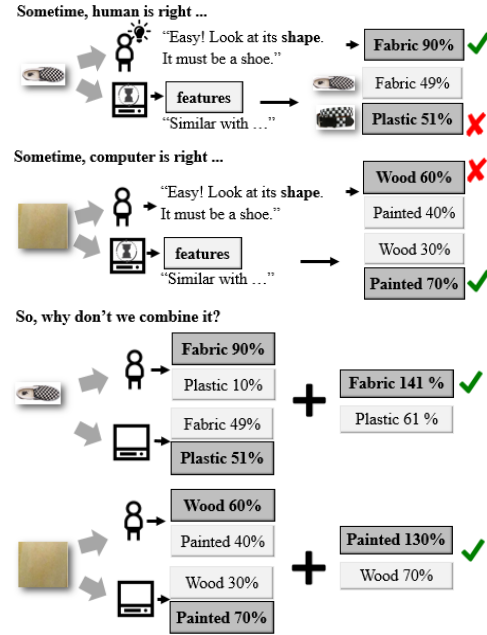

Fig. 4: We consider that deep feature extracted from a CNN can represent for the way human think and learn. Combine it with a suitable handcrafted feature would improve the prediction.
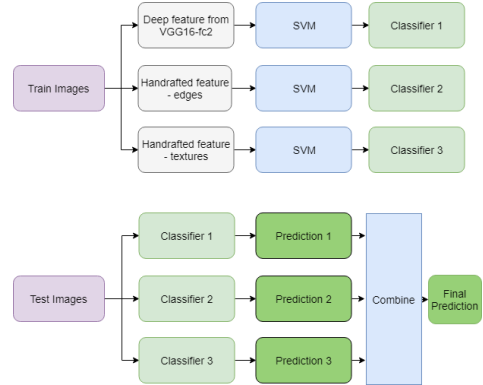

Fig. 5: Method 1: Combine probability predictions

The second method combines three branches after features have been extracted to get only one final feature vector for each sample, then use the combined features vector for training and predicting as usual. Features are combined by vector concatenation (see figure 6).

The third method is a mixed architecture of two above. The original image will go by it own on the first branch and also combine its features with remain input images in the second branch. Final prediction would be an averaging combination of two branches. This approach gives the best performing in three methods.Both combination methods (for features combination, prediction combination) and variations of handcrafted features we may choose for particular task or dataset make the architecture more flexible and effective (see figure 7)..
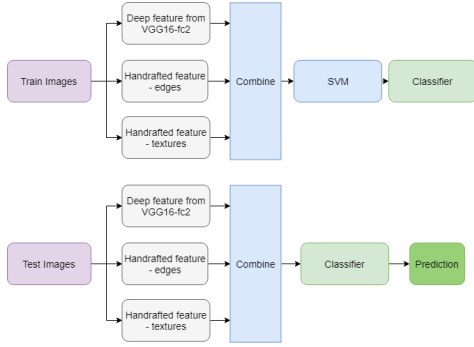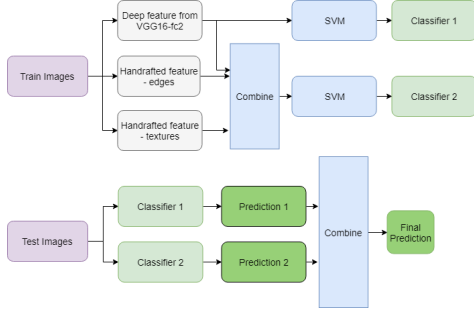
Fig. 6: Method 2: Combine features

Fig. 7: Method 3: Mixed of method 1 and 2, the best performing architecture

IV. EXPERIMENTS

We evaluate our method on newest material dataset Ground Terrain in Outdoor Scenes Dataset (GTOS) [10] and another common dataset from Flicker (Flicker Material Dataset - FMD) [13] and compare them with other state-of-the-art methods to see how handcrafted affect on different dataset. For each dataset, we firstly evaluate with different architectures to determine which method has best performance, then compare results with different features combination to show that suitable handcrafted features could be used to improve prediction result using deep feature from CNN.

Datasets: As mentioned above, our evaluation considers two datasets: GTOS and FMD. GTOS is the newest material dataset published in 2017 by the Rutgers ECE Vision Lab. Consisting over 34000 images covering 40 classes of outdoor ground terrain under varying weather and lighting conditions, this is one of the most extensive dataset for the task. In this paper, we use pre-processed images (includes crop size, subtracting a per color channel mean and and normalizing for unit variance - for detail, you can find it at [10]) for training and testing.

On the other side, FMD has been one of the most common dataset for material classification from the very beginning of the task (2009).

Note that the size of all images in both datasets is 224 x 224.

Evaluation measures: In particular, for both dataset, evaluation uses average classification accuracy.
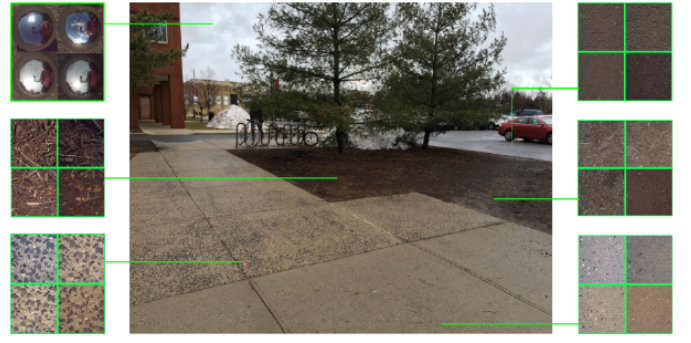

Fig. 8: Outdoor scene surfaces imaged example from GTOS dataset with multiple viewpoints, illumination conditions [10]
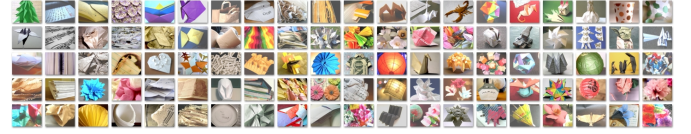

Fig. 9: Examples from FMD dataset, ensure a variety of illumination conditions, compositions, colors, texture and material sub-types

Training process: We use splits from the previous research which assign 70% for training - 30% for testing on GTOS and these rates are 80% - 20% for FMD. First, from the original images, we extract edges with Canny edges detection and textures with local range texture filter. For deep feature, we use Keras framework (with Tensorflow as back-end) to extract deep feature from layer "fc2" of a VGG16 Image-Net pre-trained network. The training has been done with SVM from Scikit-learn frame work. The combination for features is vector concatenation and for final probability prediction is averaging.

Evaluation: The table 1 and 2 shows the mean accuracy (%) of three approaches mentioned in Method section on GTOS dataset.

Method	Deep feature	Deep+edges	Deep+edges+textures
Combine prediction	75 ± 1.8	75.5 ± 3.0	76.3 ± 1.9
Combine features	75 ± 1.8	77.8 ± 2.5	79.5 ± 2.5
Mixed two above	75 ± 1.8	78.9 ± 2.2	$\mathbf{82.2 \pm 2.3}$

TABLE I: Evaluation on GTOS dataset. The table compares results on different method of combination and different features (also deep feature only vs deep feature combines with other handcrafted features).

Method	Deep feature	Deep+edges	Deep+edges+textures
Combine prediction	74.2 ± 1.4	75.1 ± 2.2	75.5 ± 2.3
Combine features	74.2 ± 1.4	75.3 ± 1.5	76.3 ± 1.7
Mixed two above	74.2 ± 1.4	75.5 ± 1.2	$\mathbf{77.2 \pm 0.9}$

TABLE II: Evaluation on FMD dataset

Method	GTOS	FMD
DAIN	81.2	
Reflectance		65.5
Ours	**82.2**	**77.2**

TABLE III: Comparison with other methods on GTOS and FMD datasets [10] [11]
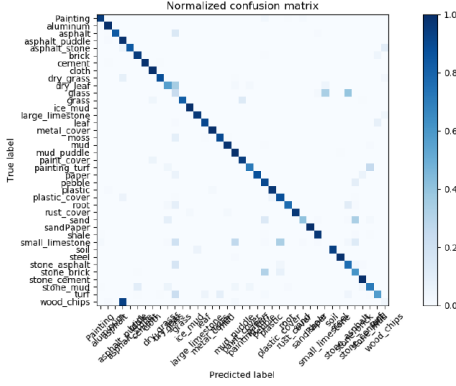

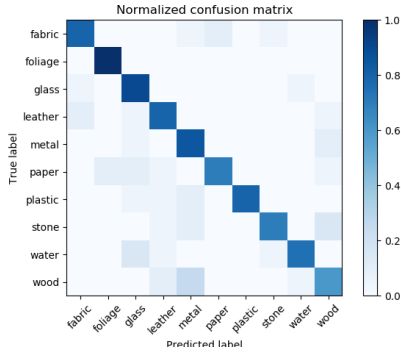Fig. 10: Normalized confusion matrix of best result on GTOS dataset

Fig. 11: Normalized confusion matrix of best result on FMD dataset

V. CONCLUSION

In this paper, we investigate how handcrafted features can be used with deep feature learned from a trained CNN to improve material classification on 2D color image which often reply on object classification to predict material. We compare the performance of different architectures exploiting different types of input information as handcrafted features, and the results show that, the two streams architectures which combine both features and predictions is the best one for classification in GTOS and FMD.

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