Using GelSight Sensor for Material Recognition in the Wild

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Abstract

Humans can rapidly categorize materials such as fabric, wood, metal and plastic by using visual or tactile sensory systems. Material perception has been widely studied as a visual recognition problem. As per our knowledge, most of the work in material perception uses visual data – often neglecting other sensory data such as tactile feedback. This neglect is primarily due to lack of easy availability of tactile sensors. GelSight is a novel tactile sensor technology that can provide detailed and rapid surface measurements of any physical object. We use GelSight sensor to create a dataset of material categories from real world objects that include – Fabrics, Foliage, Stones and Wood. We primarily collect RGB images depicting the microscopic view of materials and also the 3D reconstruction of the surface properties of the material through the GelSight sensor. We propose using globally weighted Linear Binary Pattern $(LBPV)$ features and 3D shape features (SF) to classify material category for novel data. The classification rate using our proposed algorithms is: Fabrics, Foliage, Stones and Wood. It is clearly evident from the LBPV classification results that material perception through tactile data is not just a texture problem but needs 3D shape information for some material categories.

1. Introduction

One of the goals of the human visual system is to infer rich structural properties of the world from visual scenes. In order to infer these properties, the visual cortex can semantically and syntactically parse visual scenes. Object recognition is one way to realize such a scene parser – where the visual cortex could aggregate detected objects to form perception. On the other hand, there is a lot of visual $stuff$ in the world which cannot be handled by current object recognition systems. For example, a leather and plastic shoe belong to the same object cateogry but not the same material category.

Humans can infer material categories by $looking$ and $touching$ physical objects. However, material recognition using tactile data has been largely unexplored. However, with the advent of GelSight sensor, which can provide cheap, fast and robust surface measurements from objects, it has now become possible to tackle this problem in the tactile domain (Fig 1). The GelSight sensor has a proprietary gel that deforms in accordance with the physical object that it touches at any given point of time. This gel magnifies the surface of the object and "covers" it with it's own surface BRDF. A camera overlooking this gel takes six photographs, where in each photograph, the light direction that illuminates the gel varies it's source direction automatically. A photometric stereo method developed by [?] can then by used to obtain the 3D reconstruction of the surface properties of the object.

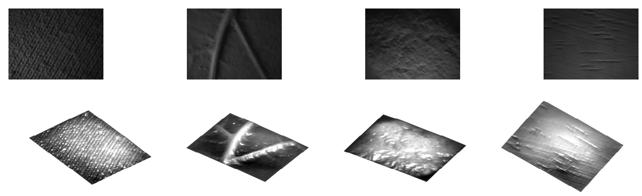


Figure 1: TODO

We use both the RGB and 3D shape images obtained from the GelSight sensor and propose two different material classification algorithms. The RGB images (Fig 2) obtained from the sensor are under varying illumination conditions. We fix the illumination condition and construct a dataset of such images for different material categories. These images reflect the microscopic structure of materials under known BRDF, which is calculated by a calibration technique given in [?]. Given this image dataset, the problem of material classification can be posed as a texture recognition problem. We use LBPV features, proposed by [?], to encode texture. Linear Binary Pattern (LBP) features are widely used to encode local texture properties. Authors of [?] have recently proposed weighted LBP, which is called as LBPV, which uses global variances as weights for LBP value at each pixel. Thus LBPV capture the local as well as global texture properties in an image. We use a supervised learning

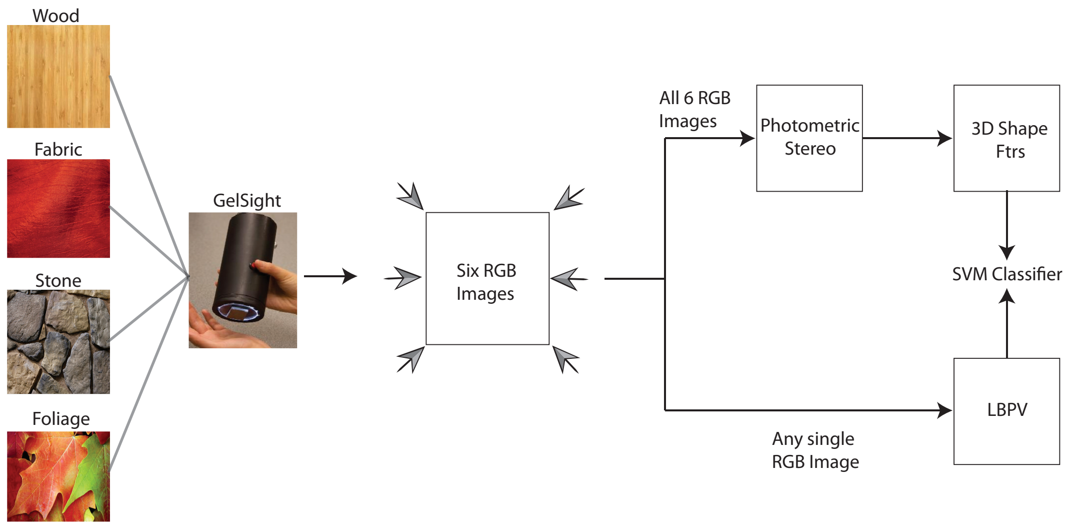


Figure 2: TODO

algorithm (SVM) to learn a material classifier using LBPV features. We learnt that for material categories without repeating patterns (Fig 3), textures do not provide a good feature representation to perform material classification. This led us to use 3D shape information to classify material categories. The main contributions of this paper are:

- One of the first attempts to model tactile based material perception as a vision problem for challenging material categories
- Best features to encode GelSight data for material recognition
- Real-time execution of material classification, which is important for robotics applications among others.
- Challenges current view that tactile based material perception is primarily a texture problem. Results indicate that additional information such as 3D shape may be very important.

2. Related Work

Several groups have been trying to solve material recognition using visual data [?]. One of the leading methods to classify materials make use of bayesian inference to detect materials from images [?]. In this method, several discriminative features such as SIFT and color are used, and the clusters of these features are modelled using LDA for classification. On the other hand, we are not aware of direct work done in material perception using tactile information alone. This is primarily due to the lack of availability of good sensors to capture tactile data. With GelSight, it has been very easy and cheap to get access to such tactile data and model it as a vision problem. Additionally, various groups have studied texture recognition, which is interesting for tactile based material perception [**?**, **?**]. We shall use ideas from [**?**] to build one of the features for our material classifier.

2.1. Miscellaneous

Compare the following:

`$conf_a$` $conf_a$
`$\mathit{conf}_a$` conf_a

3. Our Approach

Material recognition is an important human perception problem. As described earlier, there are several methods to build a material classifier using visual data. However, humans are also able to infer material categories by the sensation of *touch*. We shall explore the limitations of tactile based material perception using a simple **black-box text**. [1]

3.1. Calibration

Figure 3: TODO

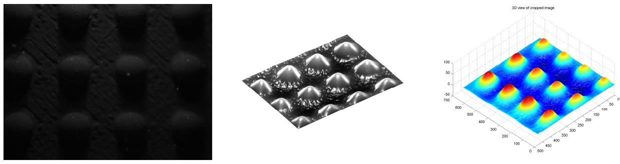


Figure 4: TODO

Method	Frobnability
Theirs	Frumpy
Yours	Frobbly
Ours	Makes one's heart Frob

Table 1: Classification Results. TODO

3.2. 3D Shape Features

TODO

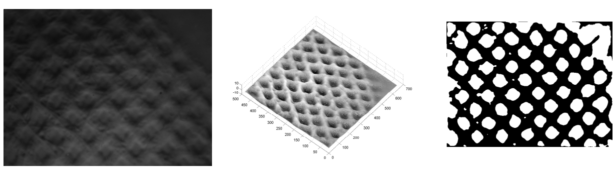


Figure 5: TODO

3.3. Classification Performance

TODO

3.4. F

ast LBP Implementation TODO

4. Experimental Results

TODO

4.1. F

ailures

4.2. BLAH

4.3. Illustrations, graphs, and photographs

When placing figures in LaTeX, it's almost always best to use `\includegraphics`, and to specify the figure width as a multiple of the line width as in the example below

```
\usepackage[dvips]{graphicx} ...
\includegraphics[width=0.8\linewidth]
                {myfile.eps}
```

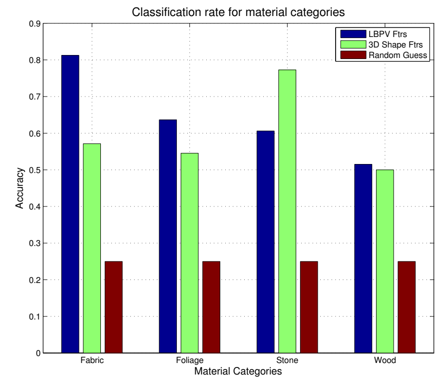


Figure 6: TODO

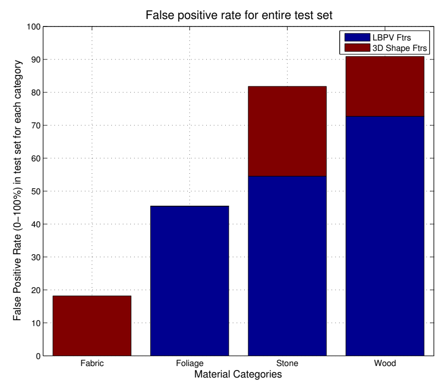


Figure 7: TODO

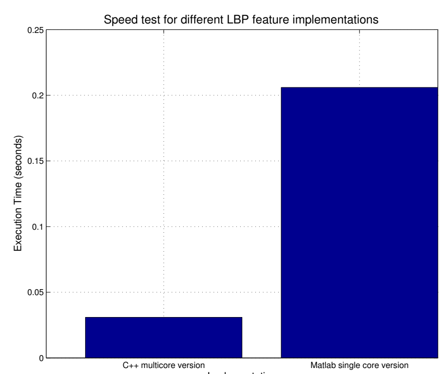
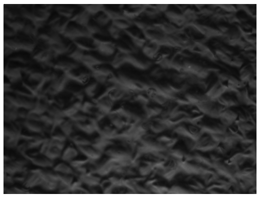


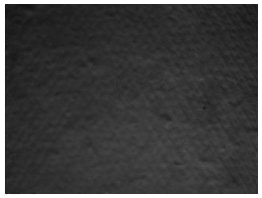
Figure 8: TODO

5. Conclusion

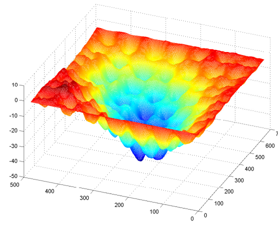
Color is valuable, and will be visible to readers of the electronic copy. However ensure that, when printed on a



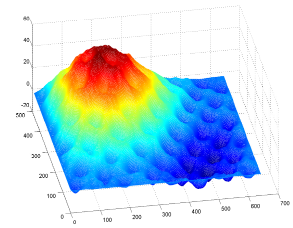
(a) MH with blur and displaying "left" RV of one box



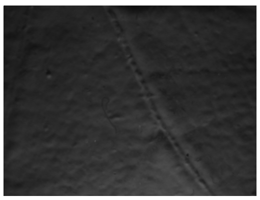
(b) Gibbs with blur and displaying "left" RV of one box



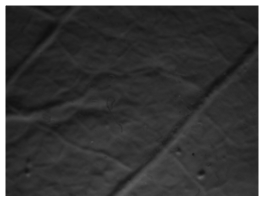
(c) MH without blur and displaying "left" RV of one box



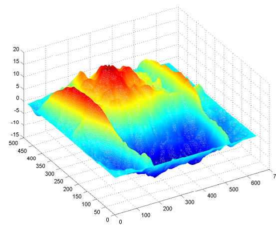
(d) MH sampling without blur and displaying "left" RV of one box



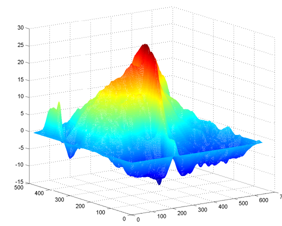
(e) MH with blur and displaying added "left" RV from multiple boxes



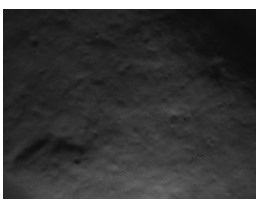
(f) Gibbs with blur and displaying added "left" RV from multiple boxes



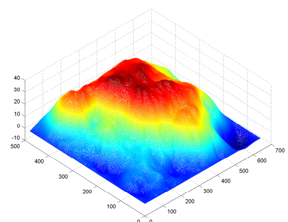
(g) MH without blur and displaying added "left" RV from multiple boxes



(h) MH sampling without blur and displaying added "left" RV from multiple boxes



(e) MH with blur and displaying added "left" RV from multiple boxes



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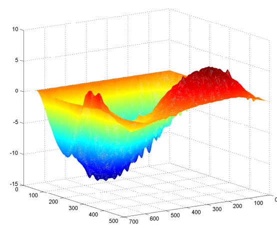

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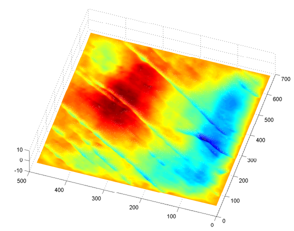

(h) MH sampling without blur and displaying added "left" RV from multiple boxes

Figure 9: TODO

monochrome printer, no important information is lost by the conversion to grayscale.

6. Acknowledgements

You must include your signed IEEE copyright release form when you submit your finished paper. We MUST have this form before your paper can be published in the proceedings.

References

[1] L. Skedung. Tactile perception - role of physical properties. *Thesis, KTH Royal Institute of Technology, Sweden*, 2010.