A Survey on Computer Vision-Based Material Perception Techniques (Postprint)

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Abstract

Material visual perception is an important prerequisite for intelligent robots to interact with the environment, and also a fundamental topic in the field of computer vision. Unlike object recognition, due to the variability in materials' external manifestations, material visual perception has become a new challenge in the field of computer vision in recent years. This paper surveys the main research achievements on the material perception problem in computer vision from both domestic and international sources, introduces the primary methods of these studies along with their typical algorithms and fundamental ideas, and summarizes two main research approaches for material visual perception: material recognition and classification, and material attribute and parameter estimation. Finally, it presents the key issues existing in current research and points out potential future development directions for material visual perception.

Full Text

Preamble

Survey on Material Perception via Computer Vision

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Abstract: Material visual perception is a crucial prerequisite for intelligent robots to interact with their environment and represents a fundamental topic in computer vision. Unlike object recognition, material visual perception has emerged as a new challenge in computer vision in recent years due to the high variability in material surface appearances. This paper surveys major research achievements in material perception via computer vision, introducing the primary methodologies, typical algorithms, and underlying concepts. We summarize two main research approaches for visual material perception: (1) material recognition and classification; (2) estimation of material properties and parameters. Finally, we identify several key issues in current research and point out potential future directions for visual material perception.

Keywords: material perception; computer vision; visual perception; material recognition; material properties

0 Introduction

Research on material visual perception technology holds significant importance. When manipulating target objects, robotic systems must perform adaptive grasping based on physical attributes such as weight, surface roughness, and softness [2, 3]. During robot navigation, it is necessary to determine whether roads are slippery; in production processes, it is essential to assess the freshness of food and fruit. Through material visual perception technology, robots can perceive their surroundings and interact with them like humans, adopting different action strategies for different materials: intelligently avoiding sharp edges of blades or broken glass while being less sensitive to clothing edges; handling fragile ceramic cups more carefully than plastic ones [4].

Every object is composed of one or multiple materials, and humans can readily understand its material composition at a glance. We can easily determine whether a table is made of wood, whether a computer is metallic, or whether a carpet is made of soft fibers. This ability to identify and distinguish materials and their attributes is called material perception [1]. Humans perceive materials through numerous sensory organs such as hearing, vision, and touch. Computer vision-based material perception systems primarily utilize computer technology to process and analyze images of target objects, obtaining knowledge about material categories and their attributes to provide a basis for subsequent behavioral analysis and decision-making.

However, material visual perception research is highly challenging due to the vast variety of materials, diverse colors, and varying shapes. In recent years, researchers from computer science, psychology, biology, and even cognitive science have been exploring ways to enable computer vision to intelligently perceive material categories and attributes. NTT Communication Science Laboratories and MIT' s Brain and Cognitive Sciences (BCS) and Computer Science and Artificial Intelligence Laboratory (CSAIL) have studied how to judge material surface attributes such as glossiness and reflectivity through grayscale statistics and sub-band filter outputs [5]. Since then, numerous studies have focused on estimating material attributes like glossiness [6–10], transparency [11–14], and surface roughness [15–20]. Sharan [1] demonstrated through experiments that humans can identify material categories from object images, with recognition accuracy significantly improving when comprehensively utilizing multiple types of information from images. However, what specific information the human visual system utilizes during material recognition remains unclear [4]. To reveal the underlying principles of human material visual perception, many biological vision experts have recently conducted research in this area. Okazawa et al. [21, 22] extracted complex texture statistics from objects and developed a series of representations. Some researchers have used functional magnetic resonance imaging (fMRI) to link early visual cortex areas and parahippocampal regions with material classification representations, though these representation models remain poorly resolved.

In fact, human capabilities in object recognition and material visual perception are not far apart. However, in computer vision research, material visual perception lags far behind object recognition in terms of both recognition accuracy and research literature volume [23–25]. Compared to object recognition, face recognition, and scene recognition, material visual perception research is still in its infancy [26], with researchers merely applying conventional methods to material visual perception. How to propose novel and effective methods to extract robust material features based on the characteristics of materials themselves remains a very new and challenging problem.

1 Material Visual Perception System

In computer vision system architecture, the general processing flow is from image acquisition to image processing to image recognition. The material visual perception system follows a similar process, with the difference being that image processing is divided into low-level image processing, mid-level image processing (estimating material attributes), and high-level image processing (high-dimensional feature space), as shown in [Figure 1: see original paper].

Low-level image processing refers to extracting local image features, such as grayscale statistics in different directions, spatial frequency, and color features. This stage primarily describes the information of the image itself without describing the physical meaning of the real world implied by the image. Then, grouping processing is performed based on relationships between features, with pooling and comparison in large neighborhoods to create more complex (typically nonlinear) responses. At this processing stage, the visual system can recognize composite features such as corners, texture gradients, and illusory contours. Although these features lack semantic information, they can describe richer image information compared to simple image information like lines and stripes. From here, the system gradually enters the mid-level visual processing stage. In this stage, the output responses from earlier stages are pooled, grouped, and compared so that the visual system can begin to formulate distal scene structure (i.e., decomposing surface illumination intensity gradients into illumination maps and reflectance maps). This blind source separation technique is essential for crossing from the stage of describing primary image features to stably identifying material attributes. The ultimate goal of mid-level vision is to describe surface characteristics such as glossiness, texture, transparency, and possibly other physical properties like hardness, roughness, or viscosity. Thus, different attribute values estimated in the mid-level visual stage are used to establish a high-dimensional feature space representing different materials, with each material represented as a point in this feature space. The specific process is as follows: given a material image patch, it has a series of estimated values for matte reflectance, specular reflectance, opacity, etc., with each estimate representing one dimension in the high-dimensional space. This entire process provides the foundation for high-level vision, i.e., clustering different material samples based on their positions in the high-dimensional feature space. The goal of high-level vision is to organize and understand the relationships between distal stimuli, thereby achieving material recognition and extracting relevant semantic information.

2 Research Status of Material Visual Perception

Currently, there are no domestic surveys on material visual perception. This paper first introduces the material visual perception system and its workflow. Then, according to different research directions, we survey current research achievements from two directions: material recognition and classification, and material attribute and parameter estimation. Finally, we propose key issues in material visual perception research and point out possible future development directions.

Based on different research directions, material visual perception research methods can be divided into two categories: (a) material recognition and classification; (b) material attribute and parameter estimation. Material recognition and classification is a top-down approach that uses object recognition methods to identify materials and then infers their attributes and parameters. For example, when people recognize that a target object is a glass cup, they can infer its transparency, hardness, roughness, and other information. Conversely, material attribute and parameter estimation is a bottom-up approach that uses mid-level image processing to obtain material attributes and parameters before performing material recognition, such as using attribute information like transparency, hardness, and roughness to identify whether the target is glass, as shown in [Figure 2: see original paper]. These two methods are not mutually exclusive but rather mutually reinforcing. Each material attribute or parameter represents one dimension of information about the target object in high-dimensional feature space; conversely, material categories help infer material attributes or parameters [27].

2.1 Material Recognition and Classification

One of the primary functions of material visual perception is its recognition and classification. Naturally, researchers consider using existing object recognition and scene recognition methods for material recognition and classification, reducing material visual perception to the relatively mature problem of object recognition. For instance, coffee cups are commonly made of ceramic, cars are made of metal and glass, and chairs are often made of wood. Using object recognition methods for target detection in images makes it easy to infer the material type of the target object. However, applying existing object recognition and scene recognition methods to material recognition also presents problems. The mapping between object categories and material categories is not one-to-one, especially for man-made products, as shown in [Figure 3: see original paper]. The same object can be made of different materials, while different objects can be made of the same material, as shown in [Figure 4: see original paper]. Unlike object and scene recognition, finding reliable features for material recognition in images is very difficult.

Although computer vision recognition success rates have surpassed humans in object recognition [28, 29], computer vision performance in material recognition is far inferior to humans. Some researchers believe that the reason material recognition lags behind object recognition may be the lack of training databases [26]. lists databases created by researchers in recent years for material recognition. The CUReT and KTH-TIPS databases are primarily used for material attribute and parameter estimation. Initially, some researchers used manually selected features (such as color, SIFT, etc.) fed to standard classifiers. Based on this material recognition system, Sharan et al. [4, 30] downloaded 1,000 images from the internet (comprising 10 materials, with 100 images per material) to establish the Flickr Material Database (FMD). This database has become a classic for human and computer material recognition. Through volunteer experiments, Sharan and colleagues found that humans can accurately identify real materials from fake ones in as little as 40 ms [31–33]. Based on human material recognition experience, Sharan et al. [34] extracted low-level and mid-level visual features that humans use during material recognition and provided them to an SVM classifier, achieving a recognition accuracy of 57%. Liu et al. [35] used the FMD database and proposed an enhanced LDA model combining low-level and mid-level features within a Bayesian framework, achieving an experimental recognition rate of 46%. Badami [36] achieved 53.1% accuracy using an SVM classifier. Subsequently, more models tended to use CNNs for automatic feature extraction. Schwartz et al. [37, 38] combined unsupervised learning and hand-selected features to achieve 48.9% accuracy. To compensate for the lack of a labeled image database like ImageNet [39] for object recognition, Wieschollek et al. [40] established the Google Material Database (GMD) and used transfer learning methods to conduct experiments on both GMD and FMD databases, achieving recognition rates of 74% and 64%, respectively. Bell et al. [41] used crowdsourcing technology to build a material database in natural environments, consisting of 3 million manually labeled region images comprising 23 materials. Undoubtedly, as material recognition databases are established and improved, they will promote the development of material visual perception.

2.2 Material Attribute and Parameter Estimation

Fleming et al. [27] invited volunteers to conduct experiments on a subset of the FMD database. These volunteers were neither explicitly told that the images came from different categories nor asked to categorize the materials, yet they achieved up to 90% accuracy in judging nine attributes helpful for material recognition. This indicates that images can be used for accurate material recognition, and material attributes are closely related to material categories. Using classification methods to categorize materials (wood, leather, glass, plastic, etc.) cannot reflect humans'rich subjective experience of materials. Computer pattern recognition technology assigns corresponding boundaries and labels to images, causing them to ignore most of the sensory features of materials [26], yet it is precisely these sensory features that make different materials appear attractive, precious, and unique. Human visual perception of materials is precisely the perception of certain inherent attributes and parameters of objects (reflectance, stiffness, translucency), which we call material attribute and parameter estimation. Material attribute and parameter estimation can be roughly divided into two categories: (a) estimation of optical properties, such as surface reflectance, glossiness, and transparency that have been extensively studied; (b) estimation of mechanical properties, such as viscosity and elasticity.

2.2.1 Estimation of Optical Properties

When light shines on an object' s surface, it may be absorbed, reflected, or transmitted. Thus, different objects exhibit different optical properties. For opaque objects, light propagation characteristics can be described by the Bidirectional Reflectance Distribution Function (BRDF) [42, 43]. This distribution function describes the distribution of reflected light in various angles after incident light is reflected, as shown in [Figure 5: see original paper]. The BRDF is defined as:

$$f_r(\theta_i, \varphi_i; \theta_r, \varphi_r) = \frac{dL_r(\theta_r, \varphi_r)}{dE_i(\theta_i, \varphi_i)} = \frac{dL_r(\theta_r, \varphi_r)}{L_i(\theta_i, \varphi_i) \cos\theta_i d\omega_i}$$

where: $\mathbf{l}$ is the incident light direction; $\mathbf{v}$ is the viewing direction; $dL_r(\mathbf{v})$ is the differential radiance reflected into direction $\mathbf{v}$; $dE_i(\mathbf{l})$ is the differential irradiance on the surface from incident light direction $\mathbf{l}$. The original BRDF model has many variables, and in practical processing, approximate analytical models with partial variables are often used to replace the original model [44–47].

Currently, research on material optical properties mainly focuses on surface reflectance perception [48–51]. Surface reflectance perception is the process of estimating unknown parameters in the BRDF from photographs. However, it remains unclear which parameters humans infer and how many parameters they utilize. Most research work only considers simple image information, though recent studies are considering image information that better expresses the real world. Real object images [5, 52, 53] and images synthesized with image software [6, 7, 27, 54-56] are used to identify real materials. Nishida, Shinya, and other researchers have shown that image information such as shape from shading is closely related to the reflectance of diffuse and specular reflection [5, 6, 53].

Most BRDF analytical models are decomposed into diffuse reflection (Figure 6: see original paper) and specular reflection (Figure 6: see original paper) components, with parameters controlling the relative proportions of these two components. The linear combination of diffuse and specular reflection can roughly estimate a range of materials with different glossiness, such as plastic, metal, and paint. However, some materials (such as velvet) cannot be expressed using this model. Generally, surface reflectance estimation is essentially the study of glossiness [57]. Recent research on glossiness mainly focuses on the following aspects: (a) measuring the invariance of glossiness under changing conditions: illumination changes [7, 8, 15], shape changes [9, 27, 54, 58, 59], and color changes [56]; (b) studying the causes of surface illumination intensity gradient changes (e.g., distinguishing surface scratches, matte shadows, and specular highlights through characteristics of surface illumination intensity gradients); (c) finding visual information for the success and failure of material visual perception [7, 60-63]. Fleming et al. [7] believe that the characteristics of illumination itself affect the ability to estimate surface glossiness. Berzhanskaya et al. [64] have experimentally proven that surface glossiness perception is spatially non-uniform and is influenced by specular highlight reflections. For translucent materials like jade and porcelain, information such as specular highlights, rendered shading, and background has a relatively large impact on glossiness estimation [11]. Anderson and colleagues emphasize the influence of geometric shape on intensity gradients [61, 62, 65], with the human visual system encoding changes in object surface normals as intensity change rates [66].

The BRDF attempts to separate reflectance and material-related information; however, this technique does not consider the influence of texture and geometric shape. Different material surfaces can present the same reflectance properties [34]. For example, glass, plastic, and wax can all exhibit transparent properties, as shown in Figure 7: see original paper. Therefore, material surface reflectance information is not a necessary condition for material recognition. Furthermore, estimating BRDF models and parameters is not an easy task. For a single image in Figure 7: see original paper, estimating its BRDF is almost impossible without simple assumptions about 3D shape or material properties [67-70, 71, 72].

The previous discussion only covered opaque objects; however, in real life, people often encounter transparent objects such as glass, water, jam, and crystal. These transparent objects cannot be described by BRDF because for transparent objects, light incident at point A will exit from other points, as shown in [Figure 8: see original paper]. This characteristic of transparent objects can be described by the Bidirectional Surface Scattering Distribution Function model. Since these objects have higher optical density than air, this leads to: (a) specular reflection, which makes most transparent objects appear glossy; (b) refraction, which causes transparent objects to appear fragmented or distorted in internal views. When transmitted light enters the object interior, part of it is scattered and part is absorbed. Scattering fills the material interior with light, making background patterns unclear and causing the material to exhibit a unique milky, slightly luminous, translucent appearance, such as marble and jade.

Most research on transparent materials idealizes the object as a transparent filter sheet, allowing the neglect of refraction and scattering effects [73–76]. When observing a surface through the filter, the resulting image patch is a fusion of background and filter colors. To perceive the inherent color and transmittance of the filter, the visual system must decompose the relative contributions of background and filter, a process called color separation. However, most transparent objects in real life are not such ideal transparent sheets, making the thin filter model lack universality. How to estimate the attributes of these transparent materials remains a thorny problem. Fleming et al. simulated glassy pebbles in front of textured backgrounds and used Maximum Likelihood Difference Scaling (MLDS) [77] to measure how refractive index changes under varying physical refractive index conditions. They discovered a nonlinear compression function that strongly correlates with the degree of background texture distortion caused by refraction. Specifically, they noted that depending on the shape of the transparent object, transmitted texture patterns appear compressed or magnified in the image. The magnitude of distortion depends not only on the refractive index but also on other scene variables such as object thickness and background distance [78]. Despite the absence of visible distortion information, people can easily identify transparent objects, indicating that humans utilize much other information when recognizing transparent object attributes. For example, since specular reflection increases correspondingly with refractive index, glossiness can be used to judge refractive index [78, 79].

To study visual information for transparency, Fleming and Bülthoff rendered materials with parametrically varying scattering characteristics. They made formal records of transparent materials and their attributes, including brightness, contrast, smoothness of intensity gradients, and color saturation. They found that translucent materials have characteristic bright stripes around corners and edges, and adding these local bright stripes to opaque objects can make their entire appearance translucent. They also measured how semi-transparency changes with illumination direction, finding that objects illuminated from behind appear more translucent than those illuminated from the front, a finding verified and extended by Xiao et al. [13]. Changing the local illumination intensity distribution of transparent materials may make them appear more opaque or transparent [5, 11]. This indicates that, like opaque materials, the human visual system can encode transparency-related information based on illumination intensity changes caused by surface shape. However, unlike opaque materials, this relationship cannot be summarized by a single reflection function that maps object surface normals to image illumination intensity [80, 81]. Marlow et al. [14] point out that the inability to obtain this mapping relationship may indicate that the surface is transparent, and that the continuity of the mapping between surface normals and intensity determines whether intensity gradients are caused by diffuse shading or transparent glow. However, many other optical phenomena (such as interreflection, cast shadows, surface texture) can also affect this mapping relationship, so how much this finding helps distinguish transparent surfaces remains questionable.

2.2.2 Estimation of Mechanical Properties

Many materials (such as textiles and fluids) are deformable, meaning they move or deform in unique ways under external forces. For example, wool or silk exhibits unique shape and motion characteristics under gravity, providing rich information for material visual perception. Wool has greater elasticity and high friction, while silk tends to be denser and smoother.

Research on material mechanical property estimation is still in its infancy. Liquids are typical materials that have sparked research interest in mechanical properties. Kawabe, Maruya, Fleming, and Nishida could infer the existence and viscosity of liquids based on motion information alone [82]. Subsequently, V. C. Paulun, Kawabe, Nishida, and Fleming inferred viscosity from static snapshots of poured liquids [83]. Woven fabrics are another important and typical deformable material. Humans can estimate the relative density and stiffness of different fabrics [84], and these properties do not change with limited external forces applied to the fabrics [85].

Research on visual information for physical reasoning, especially regarding predictions of object behavior, often requires rich internal models. When people drip honey on bread, predict the trajectory of an elastic ball, or warn friends not to place too many books on a shelf to prevent it from collapsing, these behaviors indicate that people are not simply estimating material attributes but predicting future states of materials. This aspect of material visual perception has rarely been studied [86–90], perhaps because it requires deeper representations than object recognition and attribute estimation. Object recognition (determining whether liquid exists in a scene) and attribute estimation (inferring liquid viscosity) only require judging material-related features in images. However, predicting an object' s future position, shape, and state requires some internal model that can transform current observations into future predictions in a generalized and open-loop manner.

Surface roughness estimation is relatively more mature. Currently, many surface roughness measurement techniques have been proposed domestically and internationally. Based on different measurement principles, they can be divided into methods based on optical interference principles [91–94], scattering principles [95–101], speckle principles, and machine vision-based methods [102–105]. Optical principle-based roughness measurement methods have high precision but require strict operating environments and instrumentation. Machine vision-based measurement methods offer advantages such as fast measurement speed, wide range, and relatively low cost, making them increasingly attractive to researchers.

3 Conclusion

People live in a material world composed of different materials. To enable machines to perceive the colorful real world, computer vision must leap from the low-level stage of object recognition to the high-level stage of intelligent material visual perception. However, material visual perception is extremely challenging for the following reasons:

a) The vast variety of materials, diverse colors, and varying shapes make it very difficult to extract stable features for material recognition from images.

b) Traditional visual recognition methods are not suitable for material recognition. Direct application of existing object recognition, scene recognition, and texture recognition methods to material recognition has many problems, mainly because it remains unclear what information the human visual system utilizes during material recognition. Perhaps humans do not simply use single information but comprehensively use multiple cross-level information from low-level, mid-level, and high-level stages of images, which remains worthy of investigation.

c) Databases for material recognition are very incomplete. Currently, the relatively classic material recognition database was created by Sharan by downloading 1,000 images of 10 materials from the internet. Compared to the ImageNet database for object recognition, this database is far inferior in both variety and quantity. This is also why some researchers believe material recognition lags behind object recognition [26].

Based on the above difficulties in material visual perception, future research may need to explore the following aspects:

a) Investigate from anatomy, physiology, and cognitive science which factors are crucial for material visual perception. Based on this, conduct guided processing of images, integrate low-level and mid-level visual information, extract robust material features, and lay the foundation for high-dimensional feature space representation.

b) Study new theoretical methods suitable for material visual perception. Traditional methods such as classification, matching, and parameter estimation encounter many problems in material recognition. For example, object surface reflectance properties are often related to material type, and different material surfaces can present the same reflectance properties. Therefore, it is difficult to perceive materials and their attributes visually using only material surface reflectance information.

c) Study humans' rapid generalization ability under small-sample data conditions. In many cases, people only need to see a new material once to recognize it in new environments and associate it with other familiar materials. How to enable computers to have this capability is a very worthwhile research problem.

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