Discovering the Causal Structure of Haptic Material Perception

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Abstract. The sensory signals that occur when we touch or interact with objects carry the information necessary to perceive and reason about object properties. Research on material perception has provided evidence that humans can categorize materials and assess their similarity based solely on haptic information. This evidence is based on the performance on classification tasks and correlation analyses, which, by definition, provide no information on the causes of the observed behavior. This paper explores the use of causal discovery methods to analyze human haptic perception of material categories. Causal discovery algorithms analyze statistical patterns in the data, such as conditional (in)dependence relationships, and then determine causal relationships between the variables that are compatible with these patterns. The result is a set of causal graphs with nodes representing the variables and directed edges representing empirically plausible causal relationships. In this paper, a causal discovery algorithm is used to analyze material category ratings and vibratory signals from haptic exploration. The goal is to understand the underlying cause-effect structure linking material samples, vibration signals, and category similarity ratings. The identified causal structure indicates that the information represented by the slope of the vibratory signal plays a key role in rating a material's similarity to different categories, but in parts, it is only an indirect cause. The practical use of causal discovery methods for analyzing haptic perception data is demonstrated.

Keywords: haptic perception · material category · material similarity · causality · causal discovery

1 Introduction

Humans can perceive the physical properties of objects (material and structural) by touching their surfaces thanks to the mechanical and thermal receptors located in the hand and fingertips [10]. Haptic information is necessary to perceive object properties and reason about them, for example, to make judgments about material classes or properties such as friction or elasticity [10, 3]. Research in material classification has shown that humans can categorize materials based solely on the haptic information generated during unconstrained exploratory movements in experimental settings where participants could neither see nor hear the interaction with the material samples [3, 21]. The analysis of classification performance has shown that, although humans achieve better-than-chance performance, misclassification occurs often [3, 21]. Additionally, correlation analyses have shown that perceived material categories are associated with each other [3] and that vibratory signals obtained from the classified materials are associated with haptic properties [21].

Correlations have limited explanatory power as they provide no information about the cause(s) of the observed associations between variables. Furthermore, it has been argued that results obtained in classification tasks do not provide explanations of the cognitive phenomena behind human performance [6]. These limitations can be addressed by applying causal analysis methods to identify cause-effect relationships in the data generation process of a given system. Among the different causal analysis methods, causal discovery algorithms identify the underlying cause-effect relations in data by analyzing its statistical properties [7, 6]. When applied to analyze human behavior, the learned causal relations can provide insight to understand the cognitive mechanisms that generate the observed data [11, 6].

In this paper, we explore the use of causal discovery methods to analyze human haptic perception. We apply a causal discovery algorithm to analyze the material category ratings and vibratory signals from haptic exploration provided in the *ViPer* database [21]. In particular, we are interested in the cause-effect structure that links the material samples, vibration signals, and category similarity ratings. We demonstrate the practical use of causal discovery methods for analyzing haptic perception and category similarity. To the best of our knowledge, no other study has applied causal discovery methods in the context of haptic perception of material categories.

We learn a causal structure that provides insight into the cognitive mechanisms underlying the perception of material similarity based on haptic exploration. Our results indicate that the information contained in a feature of the vibratory signal represents the information used by participants to rate a material's similarity to different categories. This feature is a direct cause for some categories and an indirect cause for others.

2 Related Work and Background

This section summarizes the sensory mechanisms that enable humans to perceive object properties from the vibrations elicited while performing exploratory movements. Subsequently, we review the features computed from vibration signals acquired during exploratory movements that represent surface properties relevant to the analysis of human perception. Finally, we provide a short introduction to causal analysis and discovery methods. We introduce the formalism used throughout the paper to represent causal models and highlight how causal discovery algorithms retrieve cause-effect relations from data that cannot be identified using associative (e.g., correlation) analyses.

2.1 Perception of Material Category Based on Haptic Exploration

When touching an object, its surface characteristics are perceived by the skin deformation patterns in the fingertips [10, 22, 5]. While coarse features can be perceived just by touching, movement is necessary to perceive fine textural features [8, 9]. Running the fingers over a surface elicits skin vibrations, which reflect the microstructure of the surface [22, 8]. These vibrations convey the information necessary to perceive fine textural properties such as roughness and to assess (dis)similarity between materials [5, 4, 22, 8]. Information about a texture's fine properties is encoded in the responses of the rapidly adapting tactile nerve fibers of type I and II, associated with Meissner and Pacinian corpuscles, respectively, which are highly sensitive to skin vibrations [5, 22, 10]. It has been observed that the ability to discriminate different textures and perceive their characteristics is independent of the speed of the exploratory movement [10, 5]. Evidence from the analysis of neural activity in primates indicates that perceptual constancy across different speeds is achieved by a systematic dilation/contraction of the spiking patterns of afferent responses [22].

Human material classification based on haptic exploration has been investigated using experimental setups where participants could freely explore different materials but could neither see nor hear the interaction [3, 21]. In a setup where participants could explore materials from seven material classes (plastic, paper, fabric, fur and leather, stone, metal, and wood) with their bare hands, it was observed that materials with similar surface properties were confused most often and that, on average, 66% of the stimuli were consistently assigned to their material class [3]. The authors conclude that haptic information alone does not allow perfect material recognition.

The perception of material category based on indirect haptic perception has been investigated using a setup where participants explored materials using a hand-held tool [21]. The tool recorded the vibration signals during the haptic exploration. After the exploration, participants were asked to rate the sample's similarity to each of the following categories: wood, plastic, fabric, paper, metal, stone, and animal. A classifier of the perceived material category was trained using the vibration signals. The slope of the signals' frequency spectrum was used as a classification feature, achieving an accuracy of 38.27% (empirical chance level = 16.67%). Based on these results, the authors indicate that perception is partly based on the signal's slope, where materials showing similar slopes can explain human misclassifications. It is important to note that when a tool (e.g., a knife) is used to explore an object, haptic perception is regarded as remote or indirect [10].

2.2 Features from Vibration Signals

Acquiring the signals that result during the material exploration enables the joint analysis of human subjective perception and the signal features (e.g., [21]). In experimental settings, measurement instruments are equipped with acceleration sensors to acquire vibration signals during haptic exploration (e.g., [18, 21, 19]). The vibration signal is typically summarized with hand-crafted features representing surface properties (e.g., hardness or roughness) [20, 19]. In contrast to the features corresponding to specific material properties, it has been proposed to use the slope of the vibration signal's frequency spectrum [21]. Based on a simulation analysis, it has been determined that the slope feature correlates with the activity of the rapidly adapting fibers of type I and II [21], which sense temporal changes in skin deformation for vibration detection and fine texture perception [10]. Additionally, it has been shown that the slope feature varies systematically between material categories and correlates with the perceived properties of the material (roughness, hardness, elasticity, and friction) [21].

2.3 Causal Models and Causal Discovery

Causal analysis methods enable the evaluation and modeling of a data-generating process in terms of cause-effect relationships. Associations, i.e., dependencies, between variables in a data-generating process might have different causal explanations. Considering two associated variables, X and Y, the following scenarios are possible: 1) X causes Y, 2) Y causes X, or 3) there is a third variable that causes both X and Y. An associative analysis describes and quantifies the extent to which variables are associated, irrespective of any existing or absent cause-effect relations. The methods specifically developed for causal analysis make use of the fact that the absence of a marginal or conditional dependence indicates (under weak assumptions) the absence of indirect or direct causal relations and thus can at least partially reconstruct the underlying cause-effect structure of a data-generation process [13, 7] .

Causal models can be expressed as Directed Acyclic Graphs (DAG) [15], where nodes represent the variables and directed edges (i.e., arrows) their direct causal relations. The nodes can represent categorical, ordinal, or continuous variables. The DAG formalism allows the inclusion of unmeasured variables (also graphically represented). The DAG arrows represent direct causation between variables. For example, $X \rightarrow Y$ indicates that any manipulation of the value of X will have a probabilistic effect on the value of Y when all the other variables are held fixed [15, 7]. $X \rightarrow Y$ also indicates that inducing changes in the value of Y (e.g., by forcing Y to take a specific value) will not affect X. The structure of the DAG implies conditional independence statements among the variables, known as the causal Markov assumption [15, 7]. This assumption states that a variable is statistically independent of its non-effects, conditional on its direct causes. Consequently, conditional independence tests can be applied to verify or validate causal relations against data [7, 2].

Given a system with two variables of interest X and Y, it would be possible to determine the underlying cause-effect relationship by conducting an experiment in which X and Y are manipulated while leaving all the other variables unaltered: while manipulating the cause variable yields changes in the effect, manipulating the effect would leave the cause unchanged. Whenever experimental data are not available and only observational data are provided (i.e., coming from an unmanipulated data-generation process), it is impossible to determine whether $X \rightarrow Y$ or $X \leftarrow Y$ from the purely statistical perspective. Causal discovery algorithms, also known as structure learning algorithms, aim to determine the causal structure that could have produced the given observational data, typically by a systematic analysis of many possible causal structures and testing probabilistic independence and dependence between the variables [7, 13, 6]. The result is a set of causal graphs with nodes representing the variables and directed edges representing the causal relationships consistent with the statistical properties of the data. The algorithms can also report un- or bidirected edges, which indicate undecidable directionality. Many algorithms have been developed during the last decades for different types of variables (discrete, continuous, or mixed data). While some algorithms assume that all the relevant variables are available in the data, others allow the possibility of unobserved(latent) variables. For recent reviews on causal discovery, see [7, 13, 23].

3 Materials and Methods

3.1 ViPer Database

The ViPer database[3] contains vibratory signals and perceptual judgments of material category similarity from haptic exploration [21]. Eleven naive participants explored 81 material samples (14 x 14 cm) belonging to seven material categories: wood, plastic, fabric, paper, metal, stone, and animal. There are twelve different material samples within each category, except for the metal category, which has only nine samples [21]. The animal category includes fur and leather samples. Participants explored the material samples with a custom pen equipped with a steel tip and an accelerometer to record the vibrations during the exploration movement. Each participant explored each material sample once, resulting in 891 exploration trials.

Participants were instructed to explore each material sample freely for 14 seconds. During the material exploration, participants wore earplugs and headphones, and their hands were occluded, so they could not see or hear the interaction with the material sample [21]. For each trial, a 1D vibratory signal of 10 seconds, computed from the 3D accelerometer signal, is provided. The vibratory signals were recorded with a sampling rate of 3200 Hz [21].

At the end of each exploration trial, participants were requested to rate the similarity of the material sample to each of the seven material categories [21].

[3] The database is publicly available at https://github.com/matteo-toscani-24-01-1985/ViPer, access 10.11.2023

The database contains the similarity ratings as continuous values ranging from 0 (very different) to 10 (very similar). Further details about the data acquisition setup are also provided in [12].

3.2 Discovery Variables

The variables processed with the causal discovery algorithm represent the factors involved in rating the similarity of a material exemplar to different categories. The variables are obtained from the ViPer database described in Sec. 3.1. The first variable is the *category*, so to say the ground truth, which describes the material category of the sample explored in each trial. It comprises 7 levels: wood, plastic, fabric, paper, metal, stone, and animal.

The second variable is the *slope* feature [21], which aims to represent the vibrations elicited during the exploration of the material sample, which carry information about its textural properties. The use of this feature to represent vibration signals has been motivated by the observation that the spectral power P of the signal is related to the temporal frequency f following a power law $P = 1/f^s$ [21]. Following the procedure described in [21], computing the natural logarithm to both sides of the equation yields $ln(P) = -s \cdot ln(f)$. Thus, the parameter s, i.e., the slope, can be retrieved by fitting a line in the transformed space. It has been shown that the *slope* feature provides a concise measure of the vibratory signals elicited during the haptic exploration of materials and is correlated with the activity of the skin afferents involved in texture perception and human perceptual category judgments [21].

Finally, the scores of the perceived similarity provided by the subjects after exploring each material sample are included in the following variables: *wood*, *plastic*, $fabric$, *paper*, *metal*, *stone*, and *animal*. These variables contain continuous values ranging from 0 (very different) to 10 (very similar).

Figure 1 illustrates a hypothetical DAG containing the variables selected for causal discovery. Subjects were presented with material samples from different categories. The actual category of each sample was unknown to the subjects. The samples were perceived through the vibration of the pen. It is assumed that materials from different categories cause distinctive vibration patterns, which are represented by the *slope* feature. This is expressed in the edge *category* → *slope*, which indicates that manipulating the material's *category* yields changes in the *slope* of the vibration signal. The vibration signal, represented by the *slope* feature, provided sensory evidence of the sample's properties. The graph represents the assumption that this evidence is directly used by the subjects in their subjective rating of the sample's similarity to the seven categories. This is expressed in the edges from *slope* to the *wood*, *plastic*, $fabric$, *paper*, *metal*, *stone*, and *animal* nodes, which contain ratings of the perceived similarity. These edges indicate that any change in the *slope* produces changes in the similarity ratings. The DAG expresses two key assumptions: that the information participants use is entirely captured by the *slope*, i.e., there is no further information on the category used to come to the perceptions (no edges from *category* to any of the seven similarity scores); and that the dependence between the material ratings is entirely captured by the slope (no latent variables explaining correlations between the ratings). This hypothetical DAG can be contrasted against the discovered causal structure described in Section 4.

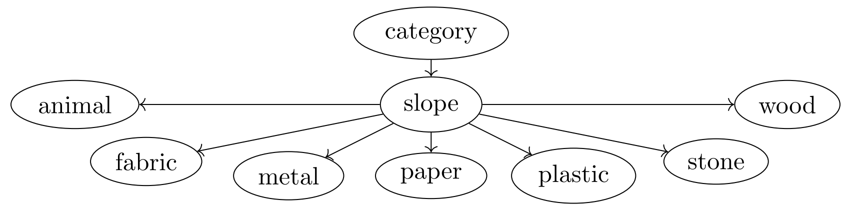

Fig. 1. Hypothetical DAG of the data-generating process of material similarity rating. The node *category* describes the category of the explored material. The node *slope* corresponds to the slope of the vibration signal. Finally, the nodes *wood*, *plastic*, *fabric*, *paper*, *metal*, *stone*, and *animal* contain the scores of the perceived similarity of the explored material to each category.

3.3 Causal Discovery Algorithm

We analyze the selected variables with the Greedy Fast Causal Inference (GFCI) algorithm [14]. This algorithm is a modification of the Fast Causal Inference algorithm (FCI), a well-established discovery method [7, 11, 13], which improves accuracy on small sample sizes. The GFCI algorithm allows for discovering causal relations in datasets containing mixed continuous and discrete data and discovering latent (also termed *unmeasured*) confounders[4]. In a nutshell, the GFCI starts with an undirected graph where all the variables are fully connected. This initial graph is pruned by performing a sequence of statistical tests to remove the edges that connect conditionally independent variables, and the remaining edges are subsequently oriented based on a set of rules (for a detailed description of the algorithm, see [14]). Table 1 summarizes the output edge types of the GFCI algorithm and the interpretation of the relationship between the variables they represent.

We use the implementation of the GFCI algorithm available in Tetrad[5] (version 7.6.1-0), a software toolbox for causal discovery [17]. In order to obtain reliable results, we chose the algorithm parameters based on configurations reported in benchmarking studies of causal discovery on mixed continuous and categorical data [16, 1]. Furthermore, we validate the stability and reliability of the causal relationships inferred from the data by performing a bootstrapping analysis [7].

[4] Given two variables X and Y, an *unmeasured confounder* is an unobserved variable U that causes both X and Y, that is, $U \rightarrow X$ and $U \rightarrow Y$.

[5] Available at: https://www.ccd.pitt.edu/tools/ , access: 29.11.23

Table 1. Graph edge types discovered by the GFCI algorithm.

Edge type	**Present relationship**	**Absent relationship**
$A \rightarrow B$	A is a cause of B. Also, there may be an unmeasured confounder of A and B.	B is not a cause of A.
$A \leftrightarrow B$	There is an unmeasured confounder of A and B.	A is not a cause of B. B is not a cause of A.
$A \circ\!\!\rightarrow B$	Either A is a cause of B (i.e, $A \rightarrow B$) or there is an unmeasured confounder of A *and* B (i.e, $A \leftrightarrow B$) or both.	B is not a cause of A.
$A\ \circ\!\!-\!\!\circ B$	Exactly one of the following holds: 1. *A is a cause of B* 2. *B is a cause of A* 3. *there is an unmeasured confounder of A and B* 4. both 1 and 2 5. both 3 and 3	
$A\ NLC\!\!\rightarrow B$	A is a cause of B and there is no latent confounder. Also, A may not be a direct cause of B.	B is not a cause of A.
$A\ DD\!\!\rightarrow B$	A is definitely a direct cause of B and there is no latent confounder.	B is not a cause of A.

We use the Degenerate Gaussian Likelihood Ratio Test (DG-LRT) [1], which has shown good performance on causal discovery with datasets containing both categorical and continuous variables and small sample sizes [1]. The decision threshold α for the DG-LRT was set to 0.01. This parameter indicates the value at which the test results are regarded as dependent. The *penalty discount* parameter controls for false positives and negative edges [16]. We set this parameter 4, as used in benchmarking studies [16, 1], where it has shown good discovery performance compared to lower and higher values. To strengthen the confidence in the discovery results, internally we also assessed the results obtained when the penalty discount is set to 3 and 5 and obtained similar results. Therefore, we report the results with the penalty discount set to 4. We also observed that setting this parameter to values ≤ 2 and ≥ 6 led to qualitatively different results, yielding DAGs with more and fewer edges, respectively, which could be due to false positive and false negative edge detections, as reported in benchmarking studies [16].

The Tetrad implementation of the GFCI algorithm allows the incorporation of background knowledge about the precedence of the variables (e.g., X occurs before Y; therefore, Y cannot cause X). Precedence is set by grouping variables into tiers, which specify the temporal order in which the variables occur. We allocate the variables in three tiers. The first tier contains the *category*, the second contains the *slope*, and the third contains the seven similarity scores.

In order to validate the causal relationships inferred from the data we performed a bootstrapping analysis. Bootstrapping provides an estimate of the stability and reliability of the causal relationships inferred from data. If the results vary widely over the different bootstrap samples, the output of the algorithm is regarded as unstable [7]. We run the discovery algorithm on 500 bootstraps with 80% of the records in each bootstrap. As a result, we obtain 500 different structures. As a summary of the bootstrapping results, we report the frequency of the edge types between variables. For ease of interpretation and comparison, the frequency of edge type is reported as a proportion of the number of bootstraps. The edge-type frequencies obtained from bootstrapping indicate whether the discovered causal relationships are stable across different samples of the data [7]. Given the different edge types (including "no edge"), we interpret an edge frequency larger than 0.5 as stable. Finally, we present a DAG which includes the stable edges, termed *discovered DAG*.

4 Results

In this section, we report the frequency of the edge types discovered by the GFCI algorithm. The frequency of the edge type is indicated in parentheses. The edge *category* $\circ\!\!\rightarrow$ *slope* (1.00) was discovered in all the bootstraps (see Fig. 2(a)). This edge indicates that the data support the assumption that material samples from different categories have an effect on the slope of the vibratory signal.

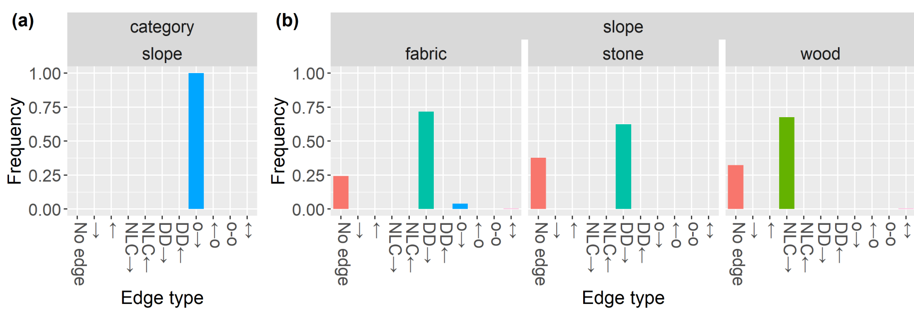

Fig. 2. (a) Edge types between the sample *category* and vibratory signal's *slope*. **(b)** Edge types between the vibratory signal's *slope* and the category similarity scores.

Figure 2(b) shows the edge types discovered between the vibratory signal *slope* and the category similarity scores. In all the bootstraps, no edges were discovered between the *slope* and the *animal*, *metal*, *paper*, and *plastic* similarity scores; thus, they are not shown in the figure for simplicity. The edges *slope* $DD\!\rightarrow$ *fabric* (0.72) and *slope* $DD\!\rightarrow$ *stone* (0.62) provide evidence that the information represented with the slope of the vibratory signal is the direct cause of the perceived similarity. The edge *slope* $NLC\!\rightarrow$ *wood* (0.67) indicates no latent confounder, and that *slope* causes the perceived similarity to *wood*.

Figure 3 shows the edge types discovered among the category similarity scores. For simplicity, the figure only shows the variable pairs with edge types other than *no edge*. The edge *animal* $DD\!\rightarrow$ *wood* (0.67) indicates that the perceived similarity to *animal* is a direct cause of the similarity to *wood*. The edges $fabric\ NLC\rightarrow\ animal$ (0.72) and $fabric\ NLC\rightarrow\ metal$ (0.95) indicate that the perceived similarity to *fabric* causes the *animal* and *metal* similarity scores and that there are no latent confounders. The edge frequencies for the pair $fabric - plastic$ lay below 0.5 and show partly contradicting causal relations. Therefore, the evidence from the data about the $fabric - plastic$ relation is considered as unclear. The edge $metal\ DD\rightarrow\ animal$ (0.54) indicates that the perceived similarity to *metal* is a direct cause of *animal*. The edge frequencies for the pair $stone - fabric$ lie below 0.5; thus, their relation is considered as unclear. Finally, the edge $stone\ DD\rightarrow\ metal$ (0.81) indicates that the perceived similarity to *stone* is a direct cause of *metal*. In all the bootstraps, no edges between *paper* and the other variables were discovered.

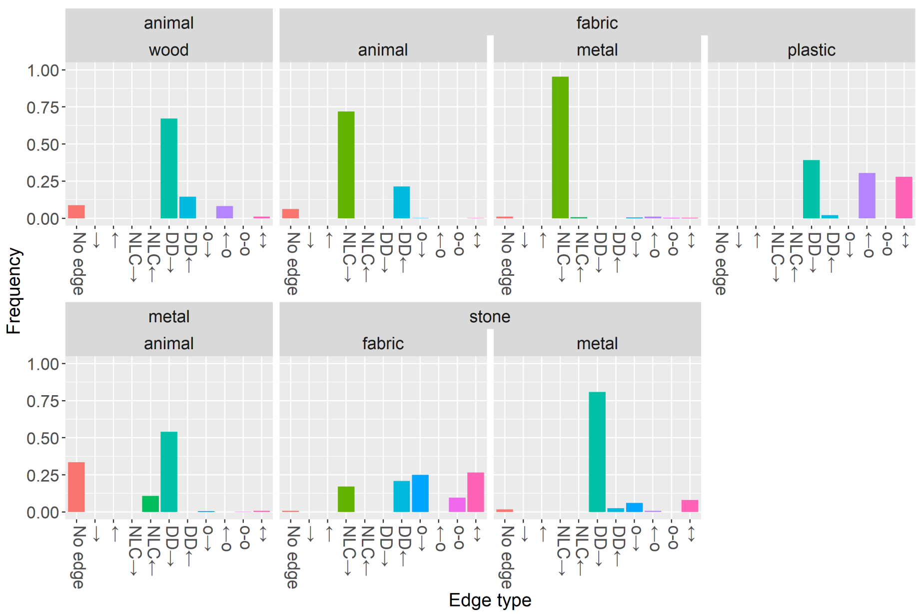

Fig. 3. Edge types between category similarity scores.

The causal discovery results are summarized in Figure 4. The results indicate that, in general, the information represented in the *slope* variable causes the perceived similarity to different material categories. This causal relationship might be direct (e.g., *slope* to $fabric$) or indirect (e.g., *slope* to *metal* via $fabric$ and *stone*). It is important to note that no edges were discovered between the *category* and the category similarity scores in all the bootstraps. This suggests that the variable *slope* mediates all the information between the material sample and the similarity scores.

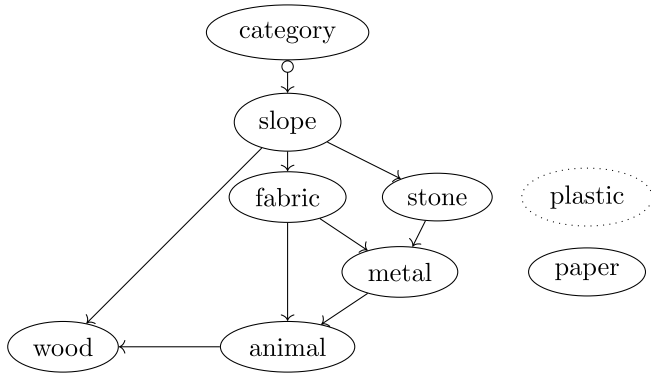

Fig. 4. Discovered DAG. The dotted node *plastic* indicates that the discovery results are unclear about its relation with other variables.

5 Conclusions

In this paper, we applied the GFCI causal discovery algorithm to a mixture of categorical and continuous variables representing the process of rating material similarity based on haptic exploration. The results indicate that *category* causes *slope*; that is, changing the category of the material sample causes a probabilistic change in the value of the vibratory signal's slope. Furthermore, the results indicate that the information represented by the slope causes the perceived material similarity. However, there may be only an indirect cause-effect relationship for some categories and none for *paper* and *plastic*. These results are consistent with previous work in which the slope has been used to classify the actual and the perceived material category [21], where it has been argued that differences in the slope can explain perception and human (mis)classifications. The discovery results differ from the hypothesized data generation process (Fig. 1) in that some similarity scores are only indirect effects of *slope*. Furthermore, the results of the causal relations between *plastic* and the other variables are unclear. This indicates that the data are too ambiguous to distinguish any edge type.

Regarding the interpretation of the discovered causal relations, it is important to recall that causal discovery methods can not demonstrate causality. Rather, the algorithms determine potentially underlying causal relations that correspond to the statistical properties of the data, specifically, the conditional (in)dependencies [7, 11, 13]. The learned causal structure can provide insights into the data-generating process. For example, the discovered edges $fabric \rightarrow animal \leftarrow metal$ indicate that the perceived similarity to $fabric$ and $metal$ causes the similarity assigned to $animal$. These causal relations suggest a structure compatible with the observed data of the internal computations performed by the subjects to complete the perceptual task. If we take the learned causal structure at face value, it suggests that humans decide (mainly using the slope) first on the similarities to $fabric$ and *stone*, and these judgments may then suggest or rule out $metal$, $animal$, and finally, *wood*. Latent variables (so other information used for the assessments not captured by slope) can, however, not be ruled out.

In addition, it has to be noted that any causal structure may be compatible with different cognitive models. For example, the causal structure may reflect a sequential process in which the similarities are determined in a particular temporal order. The similarities to $fabric$ and *stone* may be determined first, then the similarity to *metal*, and so forth. However, the similarities may also be computed in a network-like fashion, where the network activations converge towards an equilibrium state, and the causal relations reflect, e.g., a dominant influence of the $fabric$ and *stone* units on the *metal* unit.

In general, the learned causal relations can be regarded as hypotheses that can be further tested and validated, for example, by conducting further experiments [11, 7]. For example, for relations like *stone* → *metal* → *animal* (see Fig. 4) may suggest the temporal precedence of similarity judgments between categories. Thus, further experiments could be conducted to investigate the order in which subjects submit their answers or the effect of the categories' ordering in the response display[6]. The variables used for causal discovery can be further examined. We used the slope of the vibration signal as a proxy of the representation of the signal used by participants to rate the similarity of the sample to a category. Further work can be used to assess other signal features, like those proposed in [19], and determine their possible causal relation to the perceived similarity.

The results of causal discovery depend on the characteristics of the algorithm and, crucially, its parameters [7, 11]. For a given algorithm, using different statistical conditional independence tests might yield different results. We chose the algorithm based on the characteristics of the data (891 samples of mixed categorical and continuous variables) and its parameters based on benchmarking results reported in the literature [14, 1]. We followed the approach of reporting stable results over a range of settings [11]. The graph reported in Fig. 4 is based on edge types discovered with a frequency larger than 0.5 over 500 bootstraps, aiming to provide a summary of the stable discovered edges, thus informing about the confidence in the causal structure [7].

The conditions of haptic perception experiments differ from real-world situations where individuals use visual, haptic, and acoustic cues to assess material properties. It could be assumed that humans can categorize materials based on an internal haptic representation available to cope with the task. Such a unimodal representation could be constructed by enabling a learning phase where participants could establish how materials from different categories feel. However, uni-modal material categorization is likely to result from the interplay between haptic information and high-level cognitive mechanisms (e.g., memory or heuristics) in the lack of feedback or a learning phase. Baumgartner et al. [3] discuss the potential role of heuristics or lifelong associations (e.g., we always experience that metal feels cold) in participants judging category membership

[6] No details about the interface provided to the subjects to give the ratings are provided with the ViPer database.

based on uni-modal perception. The discovered causal structure provides insight into the human reasoning process behind haptic-based material perception, presenting causal relations that can be tested and validated in further experiments.

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