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Article

Active Prior Tactile Knowledge Transfer for Learning Tactual Properties of New Objects

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Abstract: Reusing the tactile knowledge of some previously-explored objects helps us to easily recognize the tactual properties of new objects. In this paper, we enable a robotic arm equipped with multi-modal artificial skin, like humans, to actively transfer the prior tactile exploratory action experiences when it learns the detailed physical properties of new objects. These experiences, or prior tactile knowledge, are built by the feature observations that the robot perceives from multiple sensory modalities, when it applies the pressing, sliding, and static contact movements on objects with different action parameters. We call our method Active Prior Tactile Knowledge Transfer (APTKT), and systematically evaluated its performance by several experiments. Results show that the robot improved the discrimination accuracy by around 10% when it used only one training sample plus the feature observations of prior objects. By incorporating the auxiliary features, the transfer learning improved the discrimination accuracy by over 20%. The results also show that the proposed method is robust against transferring irrelevant prior tactile knowledge (negative knowledge transfer).

Keywords: tactile sensing; artificial robotic skin; active tactile object perception; active tactile object learning; active tactile transfer learning

1. Introduction

1.1. Motivation

We humans perceive tactual properties of an object (e.g. stiffness, textures, temperature, weight) by applying exploratory actions (e.g. pressing, sliding, static contact, lifting). After applying different exploratory actions on an object, we can attain its different tactile information. Conversely, making the same exploratory action on different objects will produce different tactile observations. Therefore, when we learn about an object, we always link its physical properties with the exploratory actions that we apply on it.

Besides different kinds of exploratory actions, the tactile information we perceive from an object is also dependent on how we apply an action. Consider an example of pressing on two objects. The object 1 is made of soft sponge, and the object 2 is made by covering a soft sponge surface on a solid metal. When pressing our fingertips on both objects with a small normal force, we can recognize similar object deformations. However, if we press with a larger normal force, object 1 deforms much more than object 2, since we have reached the metal part in object 2. A similar situation can also be found when we apply the sliding movement on the object surfaces with different forces and velocities. As a result, by applying different exploratory actions in different ways, we can build a *detailed* knowledge of the object tactual properties which we call tactile exploratory action experiences.

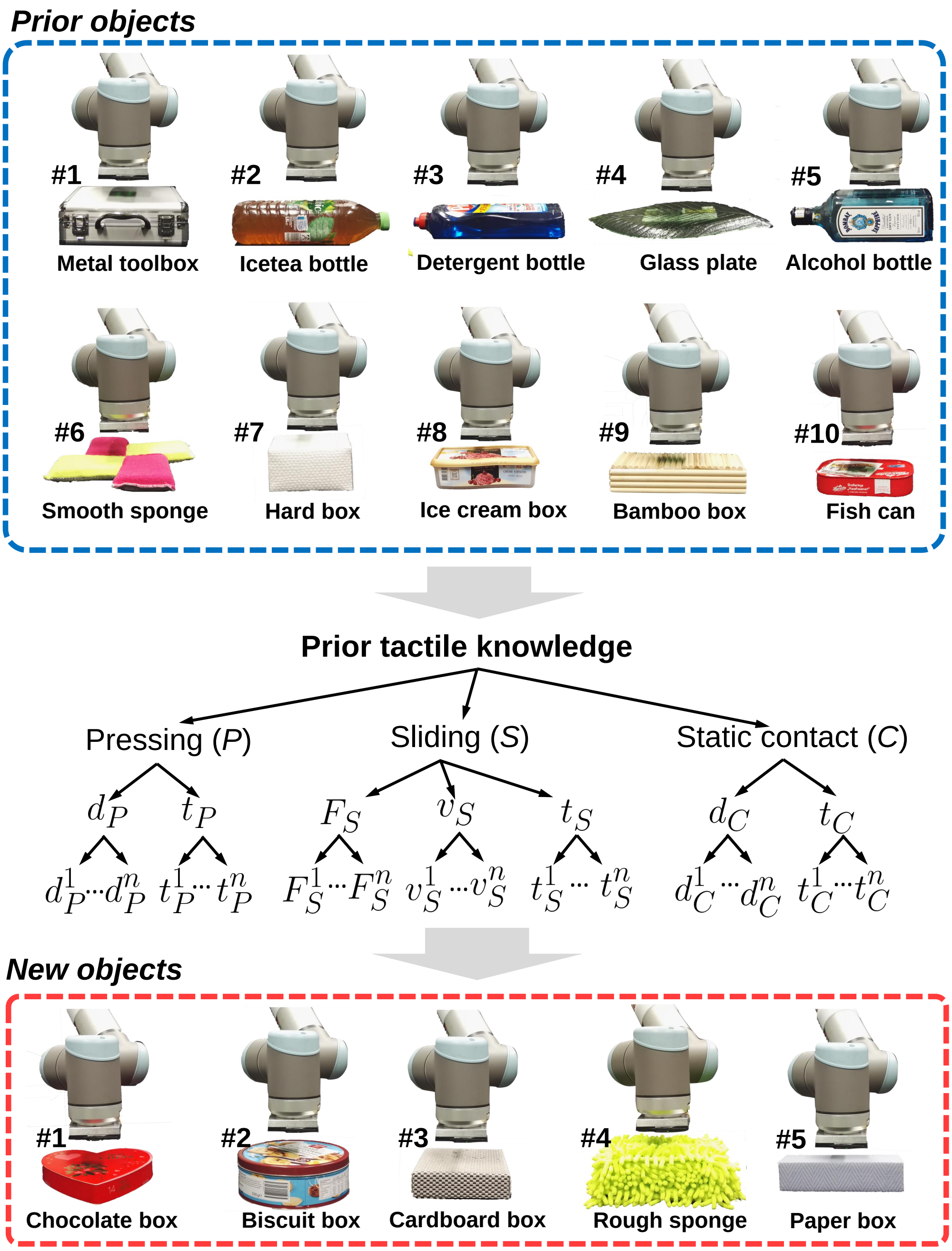

Figure 1. The robot leverages the prior tactile exploratory action experiences built by applying the pressing, sliding, and static contact movements with different action parameters on the old objects (with index #1 - #10) to learn about new objects (with index #1 - #5) physical properties. The feature observations of prior objects (prior tactile instance knowledge) were used to transfer the action experiences.

We humans learn about new objects in an active and incremental way. We actively select the most informative exploratory actions to interact with them. More importantly, we relate these new objects with the experiences of exploring the objects that we have previously encountered. By transferring the prior tactile knowledge, or prior tactile exploratory action experiences, we can largely reduce the amount of exploratory actions required to discriminate among new objects. In this way, we humans save a lot of time and energy, and recognize new objects with high accuracy.

Can robotic systems with a sense of touch also performs like humans to actively transfer the past tactile exploratory action experiences when learning about new objects (transfer learning)?

1.2. Background

Over the past decades, researchers have developed various tactile sensors and mounted them on robotic systems (e.g. [1–6]). In this way, the robots with a sense of touch can perceive different object tactual properties by applying exploratory actions. For example, a robot can slide its sensory parts on objects to sense their textural properties [7–9], build a static contact to perceive the temperature [10], or lift objects to obtain their center of mass [11]. Furthermore, several methods has been proposed for the active object exploration problem, in which the robot actively applies multiple exploratory actions to discriminate among objects (e.g. [12–17]).

However, The problem of transferring the robotic prior tactile knowledge has been rarely investigated. Even though many transfer learning techniques has been successfully applied to various areas (e.g. Natural Language Processing: [18]; WiFi-based localization: [19]; Computer Vision: [20–22]; Bio-informatics: [23]), it was our works that introduced tactile transfer learning. Previously, Kaboli *et al.* [24] developed a novel textural descriptor. Using the descriptor, a ShadowHand dexterous robotic hand equipped with BioTac sensors on its fingertips could efficiently discriminate among object surface textures. Later, we designed a transfer learning method [25] so that the robotic hand could reuse the prior texture models from 12 objects to learn 10 new object textures. However, since only the sliding movement was applied, the robot could only transfer the object textural properties. In a later work [26], we proposed an active learning method that an UR10 robotic arm with an artificial skin on its end-effector could not only apply sliding movement, but also apply pressing and static contact movements on objects to learn about their different physical properties (surface texture, stiffness, and thermal conductivity). Even though our active learning method enables the robot to efficiently learn about objects, the robot still needs to learn from scratch given a new set of objects. In this regard, recently we proposed an algorithm called Active Tactile Transfer Learning (ATTL) [27] to actively transfer the knowledge of multiple physical properties from prior objects. Using ATTL, the UR10 robotic arm could actively select prior knowledge of different object physical properties (surface texture, stiffness, and thermal conductivity by applying sliding, pressing, and static contact movements) to transfer. As a result, the robot could use less training samples to achieve higher recognition rate, when it learned about new objects.

The robotic systems in the above-mentioned works only applied exploratory actions with fixed action parameters, e.g. sliding with a fixed velocity to perceive surface textures. Therefore, the robots can only transfer limited prior tactile knowledge and learn the coarse physical properties of new objects. In order to learn objects' *detailed* physical properties so as to better discriminate among objects, the robots should be able to apply an exploratory action in different ways, similar to us humans.

1.3. Contribution

In this paper, we focus on actively transferring the prior tactile exploratory action experiences to learn the detailed physical properties of new objects. Our contributions are two-folds:

- We enable a robot to apply more exploratory actions with various action parameters. In this way, the robot gains a more detailed object tactile knowledge.
- We propose a tactile transfer learning algorithm so that the robot actively leverages the detailed tactile knowledge of some previously-explored objects (i.e. prior tactile exploratory action experiences), when it learns about new objects. The feature observations of prior objects are transferred, which are perceived from multiple sensory modalities.

In the sequel, we first introduce the robotic system (Sec. 2). Then, we illustrate how the robot applies exploratory actions and obtain the physical properties of objects (Sec. 3). Afterwards, we illustrate our proposed tactile transfer learning in detail (Sec. 4), followed by a systematic evaluation

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Table 1. Technical information of sensors in the artificial skin ([7]).

Type	Sensor	Range	Accuracy	Resolution
Proximity	VCNL4010	200mm	N.A.	0.25lx
Acceleration	BMA250	± 2g	256LSB/g	3.91 mg
Temperature	LM71	$-40 - 150°$C	$\pm 1.5°$C	31.25m°C
Normal force	customized	> 10N	0.05N	N.A.

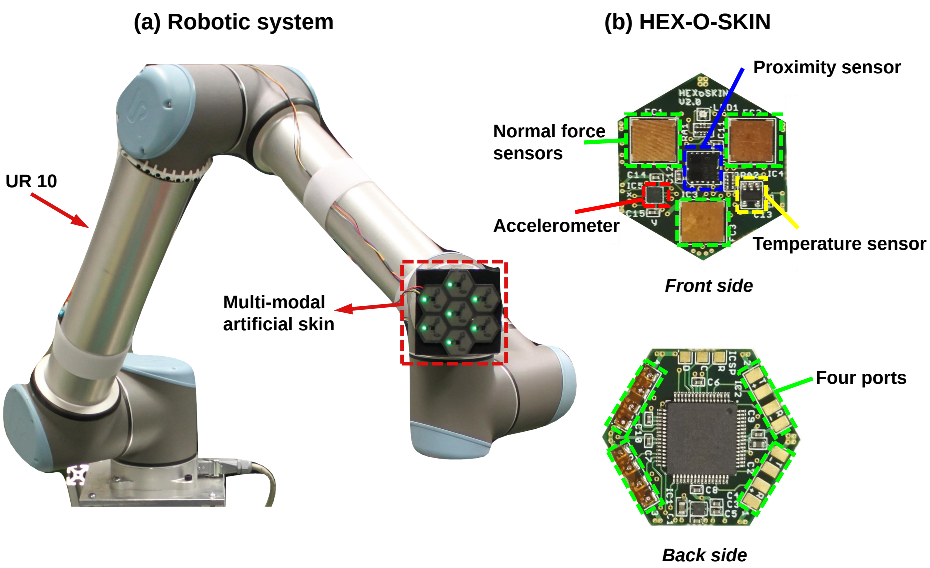

Figure 2. (a): The UR10 robotic arm equipped with a multi-modal artificial skin. **(b)**: The HEX-O-SKIN (skincell) in the artificial skin.

of the method (Sec. 5). We finalize this paper with a conclusion and a discussion about future works (Sec. 6).

2. System Description

2.1. Multi-modal Artificial Skin

To enable the robot to perform more human-like behaviours with different tactile sensing modalities, we designed and manufactured multi-modal artificial skin (Fig. 2 (a)) made by seven active tactile modules called “HEX-O-SKIN" (Fig. 2 (b)) [1]. Each module is a small hexagonal printed circuit board equipped with off-the-shelf sensors (one temperature sensor, one accelerometer, three normal force sensors, and one proximity sensor). In this way, robots equipped with this artificial skin with seven temperature sensors, seven accelerometers, 21 normal force sensors, and seven proximity sensors can emulate the human tactile sensing about temperature, vibrations, force, and light touch. Their technical information is summarized in Tab. 1.

2.2. UR10 Robotic Arm

We mounted the multi-modal artificial skin on the end-effector of an Universal Robotic Arm (UR10) with six DoF (Fig. 2 (a)). The UR10 was controlled in collaboration with the aritificial skin in order to apply different exploratory actions on objects.

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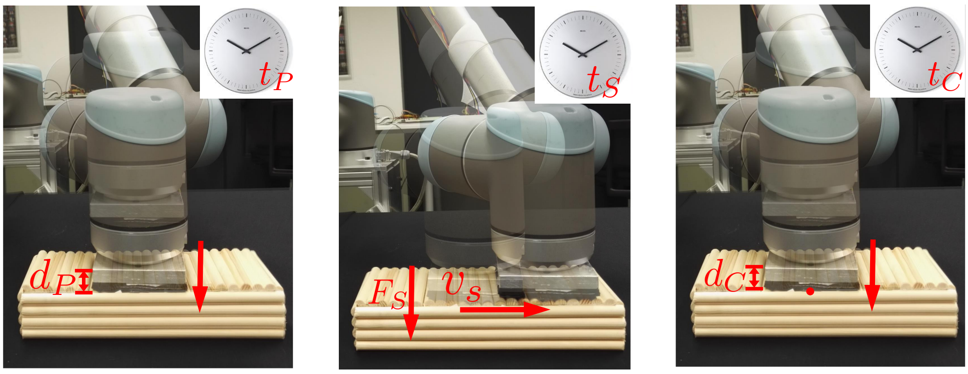

(a) Pressing (b) Sliding (c) Static contact

Figure 3. Visualization of the exploratory actions. **(a)**: The pressing movement defined by the action parameters d_P and t_P. **(b)**: The sliding movement with action parameters v_S, F_S, and t_S. **(c)**: The static contact movement defined by d_C and t_C.

3. Exploratory Actions and Perception

3.1. Exploratory Actions Definition

By applying exploratory actions on objects with different action parameters, the robot can attain different feature observations. In this work, we consider three types of exploratory actions: *pressing* (denoted as P), *sliding* (denoted as S), and *static contact* (denoted as C). Formally, we define N_a number of exploratory actions as $A = \{\alpha_n^{\boldsymbol{\theta}_n}\}_{n=1}^{N_\alpha}$, where $\boldsymbol{\theta}_n$ is the action parameters that define "how" the robot can apply the exploratory action. We further define $\boldsymbol{\theta}_n \in \{\boldsymbol{\theta}_P, \boldsymbol{\theta}_S, \boldsymbol{\theta}_C\}$, where $\boldsymbol{\theta}_P, \boldsymbol{\theta}_S$, and $\boldsymbol{\theta}_C$ represent the action parameters for the pressing, sliding, and static contact movements respectively.

3.1.1. Pressing

The robotic system presses its sensory part on the object surfaces in order to perceive its stiffness. The pressing movement consists of pressing until a depth of d_P and holding the artificial skin for t_P seconds, i.e. $\boldsymbol{\theta}_P = [d_P, t_P]$. During the pressing, the multi-modal artificial skin can record the normal force feedbacks from each normal force sensor: $\mathbf{F}_{n_f,n_s} = \{F_{n_f,n_s}^m\}_{m=1}^{t_P \cdot f_s}$ in order to measure the object stiffness, where N_f is the number of normal force sensors in one skincell (in our case $N_f = 3$), and N_s is the number of skincells in the artificial skin (in our case $N_s = 7$). Moreover, it can record the temperature feedbacks from each temperature sensor for the purpose of attaining the object thermal conductivity: $\mathbf{T}_{n_t,n_s} = \{T_{n_t,n_s}^m\}_{m=1}^{t_P \cdot f_s}, n_t = 1, ..., N_t$, with N_t being the number of temperature sensors in one skincell (in our case $N_t = 1$). f_s is the sampling rate of the artificial skin, and m the sampling time step.

3.1.2. Sliding

The robot slides the artificial skin on the object surface and perceives its textural properties. To do this, the robot first builds a contact with objects with the normal force of F_S, then it linearly slides on the objects with a speed of v_S for t_S seconds, $\boldsymbol{\theta}_S = [F_S, v_S, t_S]$. During sliding, the robot collects the outputs of accelerometers (in three axes: x, y, z): $\mathbf{a}_{n_a,n_s}^{(x)} = \{a_{n_a,n_s}^{(x),m}\}_{m=1}^{t_S \cdot f_s}$, $\mathbf{a}_{n_a,n_s}^{(y)} = \{a_{n_a,n_s}^{(y),m}\}_{m=1}^{t_S \cdot f_s}$, $\mathbf{a}_{n_a,n_s}^{(z)} = \{a_{n_a,n_s}^{(z),m}\}_{m=1}^{t_S \cdot f_s}$. Then the robot combines these signals together: $\mathbf{a} = \{\mathbf{a}_{n_a,n_s}\}_{n_a=1,n_s=1}^{N_a,N_s}$; $\mathbf{a}_{n_a,n_s} = [\mathbf{a}_{n_a,n_s}^{(x)}, \mathbf{a}_{n_a,n_s}^{(y)}, \mathbf{a}_{n_a,n_s}^{(z)}], n_a = 1, ..., N_a$, where N_a is the number of accelerometers in one skincell (in our case $N_a = 1$). Besides, the change of temperature during sliding is also collected as an extra information $\mathbf{T}_{n_t,n_s} = \{T_{n_t,n_s}^m\}_{m=1}^{t_S \cdot f_s}$.

Table 2. Exploratory actions And Perception

Exploratory actions	Action Parameters ($\boldsymbol{\theta}$)	Sensory feedbacks	Features
Pressing	d_P, t_P	$\mathbf{F}, \mathbf{T}$	$\bar{F}$, $[\bar{\mathbf{T}}, \nabla\bar{\mathbf{T}}]$
Sliding	F_S, t_S, v_S	$\mathbf{a}, \mathbf{T}$	TD, $[\bar{\mathbf{T}}, \nabla\bar{\mathbf{T}}]$
Static contact	d_C, t_C	$\mathbf{F}, \mathbf{T}$	$\bar{F}$, $[\bar{\mathbf{T}}, \nabla\bar{\mathbf{T}}]$

3.1.3. Static Contact

The object thermal cues can be attained by the robotic system by applying static contact movement: the robot presses its sensory part against the object surface until a depth of d_C and maintains the contact for t_C seconds, i.e. $\boldsymbol{\theta}_C = [d_C, t_C]$. The normal force feedbacks and temperature feedbacks are recorded: $\mathbf{F}_{n_f,n_s} = \{F^m_{n_f,n_s}\}^{t_C \cdot f_s}_{m=1}$, $\mathbf{T}_{n_t,n_s} = \{T^m_{n_t,n_s}\}^{t_C \cdot f_s}_{m=1}$.

3.2. Object Physical Properties Perception

3.2.1. Stiffness

We use the normal force averaged over all normal force sensors and time steps as an indicator for the object stiffness. For the pressing movement with pressing time steps $t_P \cdot f_s$, object stiffness can be estimated by $\bar{F} = \frac{1}{t_P \cdot f_s} \frac{1}{N_f} \frac{1}{N_s} \sum_{m=1}^{t_P \cdot f_s} \sum_{n_f=1}^{N_f} \sum_{n_s=1}^{N_s} F^m_{n_f,n_s}$.

3.2.2. Textural Property

In this work, we use the same textural feature extraction method in [26]: The vibration signals $\mathbf{a}$ in the artificial skin are used to calculate the activity, mobility and complexity, denoted as $A(\mathbf{a})$, $M(\mathbf{a})$, $C(\mathbf{a})$. We also computed the linear correlation of accelerometer signals between different directions (xy,yz,xz) denoted as $L(\mathbf{a})$. The final descriptor of textural features combines activity, mobility, complexity and linear correlation together [26]: $TD = [A(\mathbf{a}), M(\mathbf{a}), C(\mathbf{a}), L(\mathbf{a})]$.

3.2.3. Thermal Conductivity

To extract the features that describe the object thermal cues, we first calculate the average temperature sequence from all the temperature sensors: $\bar{\mathbf{T}} = \sum_{n_t=1}^{N_t} \sum_{n_s=1}^{N_s} \frac{\mathbf{T}_{n_t,n_s}}{N_t \cdot N_s}$. We then calculate its gradient at each time step as: $\nabla\bar{\mathbf{T}}$, and combine it with the average temperature sequence: $[\bar{\mathbf{T}}, \nabla\bar{\mathbf{T}}]$. To avoid curse of dimensionality, we further reduce this combination to ten dimensions via Principle Component Analysis (PCA) method and use it as the final feature to describe the object thermal conductivity.

Tab 2. summarizes the exploratory actions, the sensory feedbacks and the corresponding tactile features.

4. Transferring Prior Tactile Exploratory Action Experiences

This section describes our proposed transfer learning method (APTKT) in detail. First, we formulate our problem in Sec. 4.1. Then, we illustrate our transfer learning method, including its process (Sec. 4.3), what to transfer (Sec. 4.4), how to transfer (Sec. 4.5), from where to transfer, and how much to transfer (Sec. 4.6). The motivation of our method is demonstrated in Fig. 1.

4.1. Problem Formulation

Assume that a robotic system has gained prior tactile knowledge of some *old* objects, on which the robot has previously applied different exploratory actions with different action parameters. These prior exploratory action experiences consist of the feature observations perceived by the multiple

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sensors and observation models from the old objects. Now, the robot is tasked to learn about a set of *new* objects. Since the old objects might share some similar physical properties with the new objects, by leveraging the related tactile exploratory action experiences, the robot can learn about new objects more efficiently.

We define N_{new} number of new objects ($C^{\text{new}} = \{c_j^{\text{new}}\}_{j=1}^{N_{\text{new}}}$) the robot is tasked to efficiently learn about through different exploratory actions $A = \{\boldsymbol{\alpha}_n^{\theta_n}\}_{n=1}^{N_{\boldsymbol{\alpha}}}$ (For simplicity, we will denote $\boldsymbol{\alpha}$ as an exploratory action in the rest of the paper). In other words, the robot should actively attain object feature observations ($V_{\boldsymbol{\alpha}}^{\text{new}} = \{V_{c_1}^{\text{new}}, V_{c_2}^{\text{new}}, ..., V_{c_{N_{\text{new}}}}^{\text{new}}\}$) for each exploratory action $\boldsymbol{\alpha}$ and construct reliable observation models $V_{\boldsymbol{\alpha}}^{\text{new}} \xrightarrow{\mathbf{f}_{\boldsymbol{\alpha}}^{\text{new}}} C^{\text{new}}$. We further define the robot prior tactile experience for an exploratory action $\boldsymbol{\alpha}$ for N_{old} number of prior objects ($C^{\text{old}} = \{c_i^{\text{old}}\}_{i=1}^{N_{\text{old}}}$) as the prior object feature observations ($V_{\boldsymbol{\alpha}}^{\text{old}} = \{v_{c_1}^{\text{old}}, V_{c_2}^{\text{old}}, ..., V_{c_{N_{\text{old}}}}^{\text{old}}\}$) and the observation models of old objects $V_{\boldsymbol{\alpha}}^{\text{old}} \xrightarrow{\mathbf{f}_{\boldsymbol{\alpha}}^{\text{old}}} C^{\text{old}}$. These feature observations are collected by the multiple tactile sensors from the artificial robotic skin.

We formulate our problem as the transfer learning in the Gaussian Process Classification (GPC) framework [28], where each object is regarded as a class, and for each exploratory action, a GPC model is built as the observation model. The robot iteratively applies the exploratory actions and leverages prior tactile knowledge to improve the GPC observation models of new objects.

4.2. Gaussian Process Classification

The Gaussian Process Classification (GPC) model describes the mapping between the observation set X and the output set Y by: $X \xrightarrow{f} Y$. The latent function $g(\mathbf{x})$ in the GPC model is assumed to be sampled from a high-dimensional gaussian distribution called GP prior [28]: $g(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), K(\mathbf{x}, \mathbf{x}'))$, where each sample $g(\mathbf{x_i})$ is a random variable. In this work, we use one-vs-all multi-class classification. For each object class, a binary GPC whose output label is converted to $\{-1, +1\}$ is trained for each of the N labels: $f_n(\cdot)$. Given a new sample $\mathbf{x}^*$, each binary classifier predicts the observation probability of its label $p(y_n|\mathbf{x}^*)$. The sample is assigned to the class with the largest prediction probability $y^* = \arg\max_{y_n \in Y} \; p(y_n|\mathbf{x}^*)$.

4.3. Process

The robot following our proposed method first applies each exploratory action one time on each new object, in order to collect a small number of feature observations $V^{\text{new}} = \{V_{\boldsymbol{\alpha}_n}^{\text{new}}\}_{n=1}^{N_{\boldsymbol{\alpha}}}$ (Initial data collection). Then, the robot reuses its prior tactile exploratory action experiences to improve the observation models for *each* new object (Initial prior knowledge transfer). During this process, the robot compares the relatedness between its prior tactile exploratory action experiences and the new objects (Sec. 4.6), and chooses the most related one to transfer the old object feature observations V^{old} (Sec. 4.5). Afterwards, the robot begins to iteratively collect and combine the feature observations and update the prior tactile knowledge in order to improve the observation models. At each iteration of prior tactile knowledge updating, the robot (1) actively selects the next object and the next exploratory action in order to attain a new feature observation, and (2) updates the prior tactile knowledge *only* for the selected exploratory action. The iteration terminates when there is no improvement in the observation models of new objects. Our algorithm is demonstrated by Fig. 4.

4.4. What to Transfer

When the robotic system applies an exploratory action on objects, it perceives multiple feature observations (e.g. by the pressing movement, the robot can perceive the object stiffness and thermal conductivity). The prior tactile exploratory action experiences are built using the prior objects feature observations from multiple sensory modalities that are combined together and the corresponding GPC observation models of prior objects.

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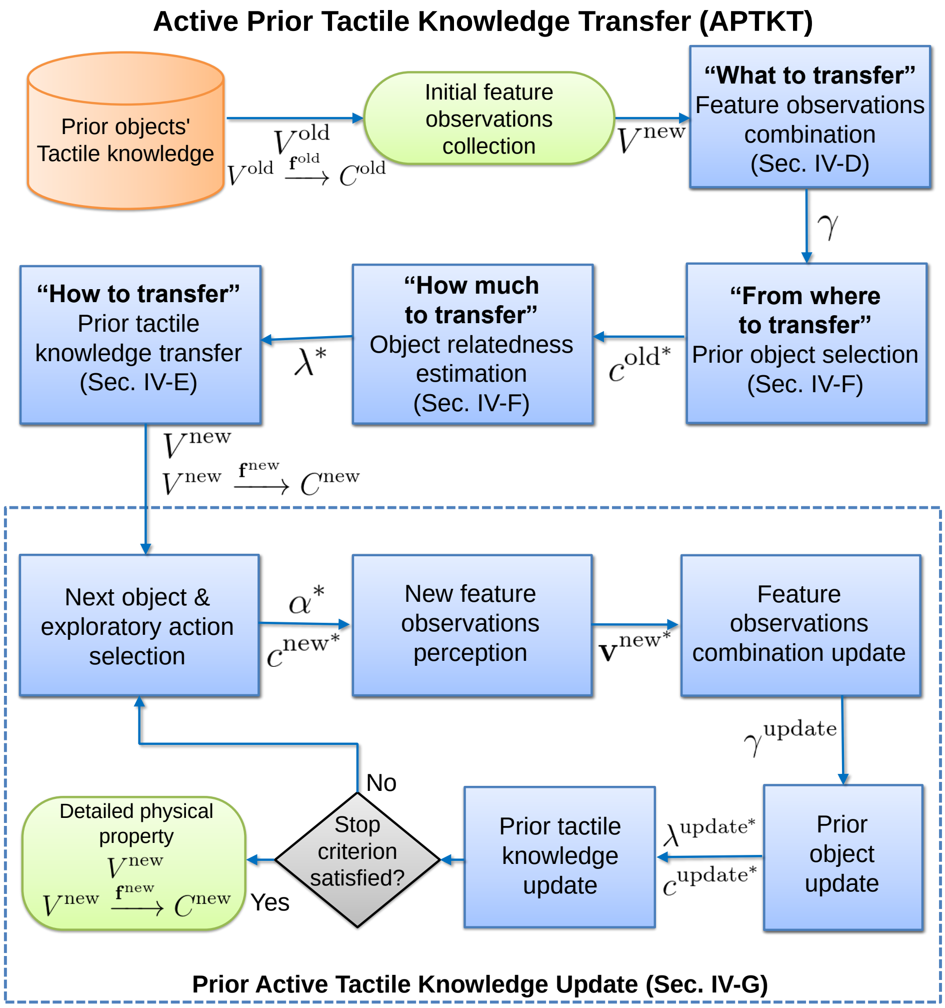


Figure 4. Flowchart of the Active Prior Tactile Knowledge Transfer algorithm.

In order to combine the observations perceived from different tactile sensors, we first define $\mathbf{v}_{\alpha}$ as the feature observation of an exploratory action α. It is comprised of multiple observations: $\mathbf{v}_{\alpha} = [\mathbf{v}_{\alpha}^{(1)}, ..., \mathbf{v}_{\alpha}^{(m_{\alpha})}, ..., \mathbf{v}_{\alpha}^{(M_{\alpha})}]$, where $\mathbf{v}_{\alpha}^{(m_{\alpha})}$ is an observation from the sensor modality m_{α}. For the pressing and static contact movements, we use the normal force and temperature sensing, for the sliding movement the accelerometer and temperature sensing (Tab. 2). Then, we assume that for a sensor modality m_{α}, a kernel function $K^{(m_{\alpha})}$ is given. To combine multiple feature observations so as to exploit the information from all sensors after applying the exploratory action α, we linearly combine the kernels:

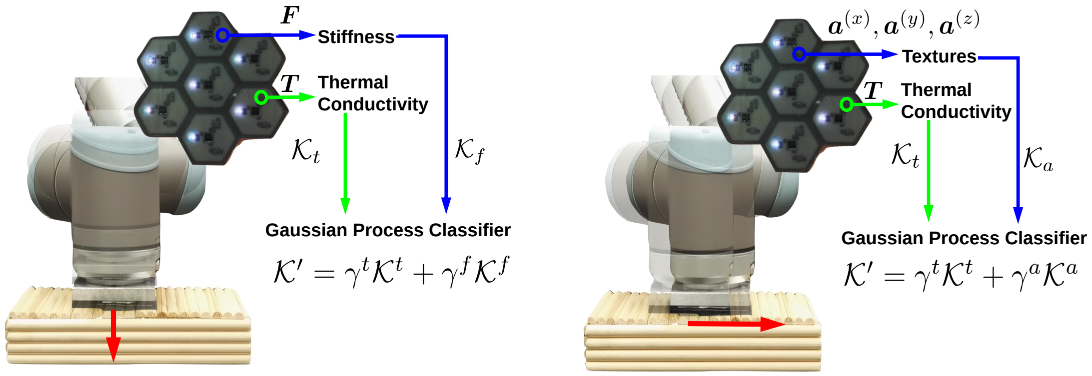
$$K'_{\alpha} = \gamma_{\alpha}^{(1)} K^{(1)} + ... + \gamma_{\alpha}^{(m_{\alpha})} K^{(m_{\alpha})} + ... + \gamma_{\alpha}^{(M_{\alpha})} K^{(M_{\alpha})} \tag{1}$$

where $\gamma_{\alpha}^{(m_{\alpha})} \geq 0$. This hyper-parameter controls how much the robot can rely on the sensor modality m_{α}. It ranges between 0 and 1, with $\gamma_{\alpha}^{(m_{\alpha})} = 0$ indicating that the sensor feedback is not informative, and $\gamma_{\alpha}^{(m_{\alpha})} = 1$ highly useful. We further constrain these hyper-parameters with L_1 norm: $|\sum_{m_{\alpha}=1}^{M_{\alpha}} \gamma_{\alpha}^{(m_{\alpha})}| = 1$. For each exploratory action, a GPC observation model is built using K'. The hyper-parameters of γ and kernels are selected by maximizing the log marginal likelihood [28]. Fig. 5 illustrates our multiple feature observations combination method. It is also demonstrated by Alg. 1.

Algorithm 1 multiple feature observations combination

Input $:C = \{c_j\}_{j=1}^{N_c}$ ▷ N_c number of objects, each object is regarded as a class.
$A = \{\alpha_n\}_{n=1}^{N_\alpha}$ ▷ N_α number of exploratory actions with different action parameters
$V = \{V_{\alpha_n,c_j}\}_{n=1,\ j=1}^{N_\alpha,\ N_c}$ ▷ feature observations
Output$:\gamma = \{\gamma_{\alpha_n,c_j}^{(m_\alpha)}\}_{\alpha_n=1,m_\alpha=1,j=1}^{N_\alpha,M_\alpha,N_c}$ ▷ Estimated sensory feedback weights.

```
for j = 1 : N_c do
    for n = 1 : N_α do
        K'_{α_n} ← γ_{α_n}^{(1)} K^{(1)} + ... + γ_{α_n}^{(M_{α_n})} K^{(M_{α_n})}      ▷ Linear kernel combination.
        {γ_{α_n,c_j}^{(m_α)}}_{m_α=1}^{M_α} ← optimizeGPC(K'_{α_n}, V_{α_n,c_j})        ▷ Finding optimal weights.
    end
end
```



(a) Pressing & Static contact (b) Sliding

Figure 5. Illustration of multiple feature observations combination method. **(a)** The robotic system combines the normal force sensing and temperature sensing to learn about objects by applying pressing and static contact movements. **(b)** The robot slides on the object surface to sense its textural property and thermal conductivity.

4.5. How to Transfer

We now describe how the robotic system transfers the feature observations of a prior object c_i^{old} to learn the GPC observation model of a new object c_j^{new}, based on an exploratory action **ff**. For simplicity, we hereby refer to i and j as c_i^{old} and c_j^{new}, respectively. We define $\mathbf{g}_i^{\text{old}}$ as the Gaussian Process latent function values [28] for the old object c_i^{old} and $\mathbf{g}_j^{\text{new}}$ for the new object c_j^{new}. We assume that these two function values are not independent from each other, but are sampled together over a dependent Gaussian Prior (GP). This dependent GP is then used to construct the GPC observation model of the new object. The latent function can be modified accordingly: $\mathbf{g}_j^{\text{new}'} \leftarrow [\mathbf{g}_i^{\text{old}}, \mathbf{g}_j^{\text{new}}]$. We further incorporate the relatedness between prior object and new object into the dependent GP model by introducing the following dependent kernel function:

$$K' = \begin{bmatrix} K(V_i^{\text{old}}, V_i^{\text{old}}) & \lambda K(V_i^{\text{old}}, V_j^{\text{new}}) \\ \lambda K(V_j^{\text{new}}, V_i^{\text{old}}) & K(V_j^{\text{new}}, V_j^{\text{new}}) \end{bmatrix} \tag{2}$$

$K(\cdot,\cdot)$ serves as the basic kernel function that measures the similarity between two feature observations that belong to the old object and the new object, respectively. $\lambda K(\cdot,\cdot)$ measures the feature observations between the old object and the new object. λ controls the relatedness between

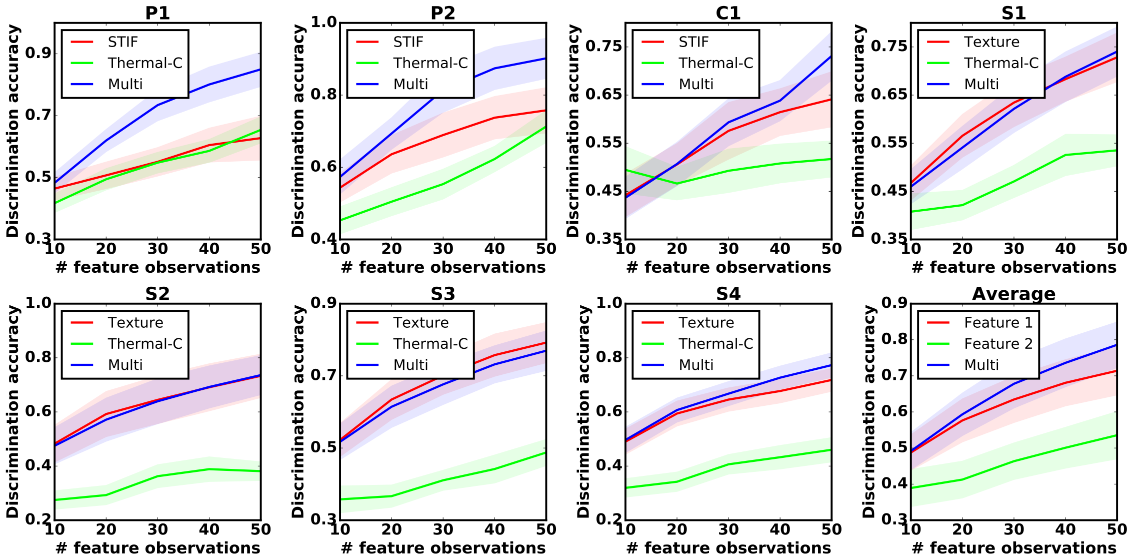


Figure 6. Multiple feature observations combination results for exploratory actions $P1$, $P2$, $C1$, $S1$, $S2$, $S3$, $S4$ and the averaged result. STIF: building the GPC observation model based on object stiffness; Thermal-C: thermal conductivity; Texture: object surface textural properties; Multi: combined feature observations. The horizontal axis represents the number of feature observations. The vertical axis represents the discrimination accuracy of the test dataset.

c_i^{old} and c_j^{new}. We constrain its range within $[0, 1]$. As Chai *et al.* [29] evaluated, $\lambda = 0$ indicates that the old object and the new object are not related, while $\lambda = 1$ indicates that the two objects are the same.

4.6. From Where and How Much to Transfer

Sec. 4.5 describes how to transfer the prior tactile knowledge to learn about new objects. This section illustrates how the robotic system selects the most related old object (from where to transfer) and how to determine the relatedness (λ) between two objects (how much to transfer). To do this, we take advantage of the prediction from the GPC observation models of old objects. Let $p(c_i^{\text{old}}|\mathbf{v}_j^{\text{new}})$ be the prediction probability that a feature observation from the new object $\mathbf{v}_j^{\text{new}}$ is assigned to the old object c_i^{old}. We measure the average prediction to all the observations $\mathbf{v}_j^{\text{new}} \in V_j^{\text{new}}$ that belong to the new object: $\bar{p}(c_i^{\text{old}}|V_j^{\text{new}}) = \frac{1}{N_j^{\text{new}}} \sum p(c_i^{\text{old}}|\mathbf{v}_j^{\text{new}})$, with N_j^{new} being the number of new object feature observations. This average prediction value indicates the similarity between the old object c_i^{old} and the new object c_j^{new}. A larger value indicates that these two objects are highly similar. Therefore, we can use it to select the most related old object (denoted as c^{old^*}) for a new object regarding the exploratory action **ff**. Furthermore, to avoid transferring irrelevant tactile information, we add a threshold ϵ_{neg} which prevents the robot from selecting any old object when the prediction value is smaller than ϵ_{neg}. The final old object selection criterion is:

$$c^{\text{old}^*} = \begin{cases} \underset{c_i^{\text{old}} \in C^{\text{old}}}{\arg\max}\, \bar{p}(c_i^{\text{old}}|V_j^{\text{new}}), & \text{if} \quad \bar{p}(c^{\text{old}^*}|V_j^{\text{new}}) \geq \epsilon_{neg} \\ \text{None}, & \text{otherwise} \end{cases} \tag{3}$$

Once we select c^{old^*}, we further use the predictions from the observation model of old objects to determine λ^*: $\lambda^* = \bar{p}(c^{\text{old}^*}|V^{\text{new}})$.

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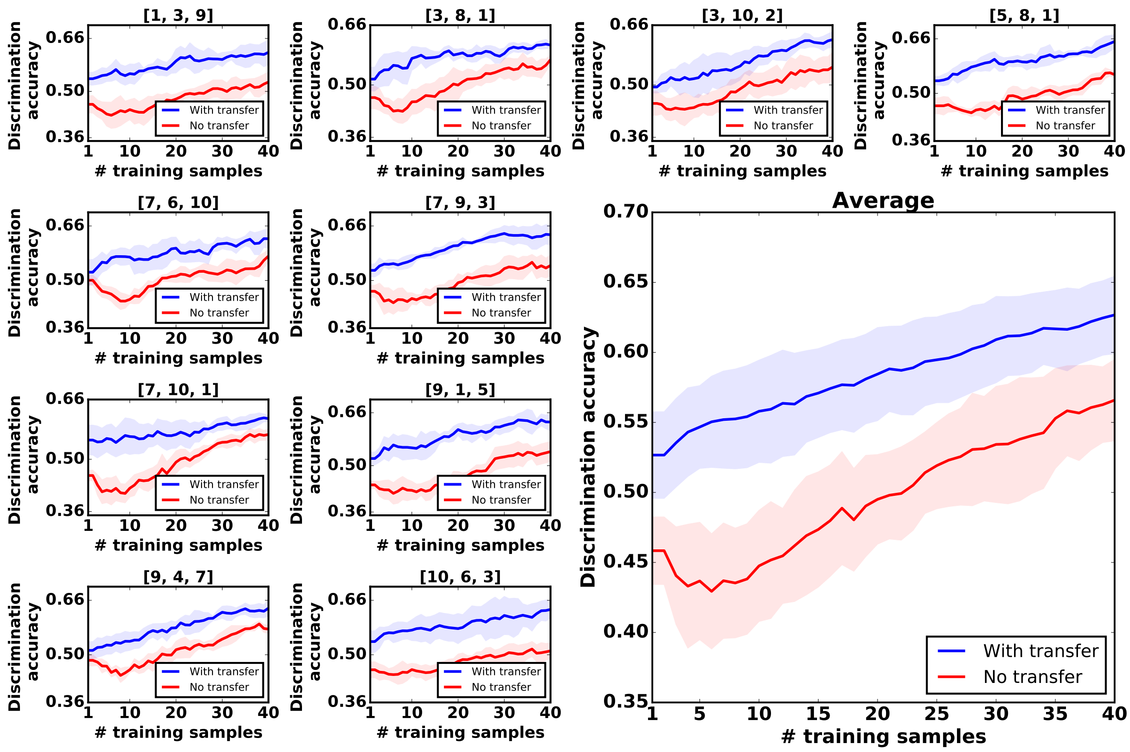

Figure 7. Transferring the exploratory actions experiences from three old objects. The small plots show the learning process from 10 groups of old objects. The large plot on the right shows the averaged results. Horizontal axis: the growing number of feature observations the robot collected. Vertical axis: the discrimination accuracy of the test dataset.

4.7. Evaluation of Multiple Feature Observations Combination Method

4.8. Prior Exploratory Action Experiences Update

When the robot updates its prior exploratory action experiences, it needs to iteratively collect a new feature observation by applying an exploratory action on an object. We use the Active Touch for Learning Physical Properties (AT-LPP) algorithm proposed in [26] so that the robot actively decides which new object to explore next (denoted as c^{new^*}) and which exploratory action to apply next (denoted as $\mathbf{ff}^*$). Once the robot collects a new feature observation, it updates the prior tactile exploratory action experiences only from action $\mathbf{ff}^*$. This process includes updating the feature observation combination, updating the object relatedness λ, and transferring these prior feature observations to the observation models of new objects.

5. Experimental Results

5.1. Experimental Objects

In order to evaluate the performance of APTKT, we deliberately selected 10 daily objects with different physical properties which served to build the robotic prior tactile exploratory action experiences (see Fig. 1 *Prior objects*). Furthermore, we selected five new objects about which the robotic system was tasked to learn (Fig. 1 *New objects*). For each new object, there existed one or more old objects that shared similar physical properties. For example, both rough sponge and smooth sponge are soft; paper box and hard box have similar surface textures; metal toolbox and biscuit box have high

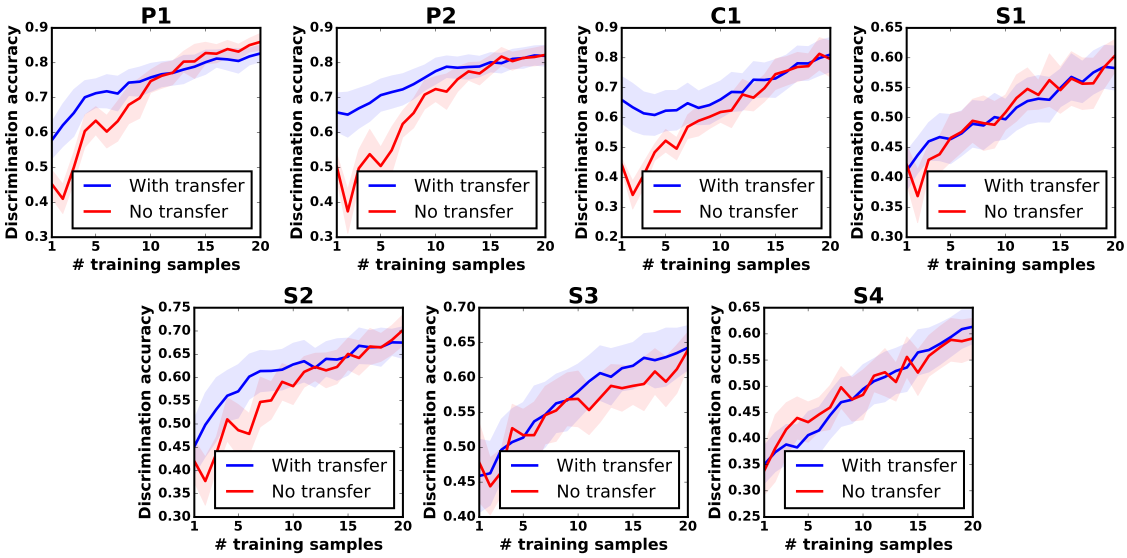

Figure 8. Transfer learning using only one exploratory action.

thermal conductivity. In this way, when learning about new objects based on their physical properties, the robot can leverage the related prior tactile instance knowledge.

5.2. Exploratory Action Determination and Test Data Collection

In our experiment, we defined seven exploratory actions from the pressing, sliding, and static contact movements with various action parameters (Pressing: $P1$, $d_P = 1$ mm, $t_P = 3$ s; $P2$, $d_P = 2$ mm, $t_P = 3$ s. Sliding: $S1$, $F_S = 0.1$ N, $t_S = 5$ s $v_S = 1$ cm/s; $S2$, $F_S = 0.1$ N, $t_S = 1$ s, $v_S = 5$ cm/s; $S3$, $F_S = 0.2$ N, $t_S = 5$ s, $v_S = 1$ cm/s; $S4$, $F_S = 0.2$ N, $t_S = 1$ s, $v_S = 5$ cm/s. Static Contact: $C1$, $d_C = 2$ mm, $t_C = 15$ s). Before applying any of the 7 exploratory actions, the robot established light contact with the objects which, detected once the total normal force on the the artificial skin increased above 0.05 N. Furthermore, after applying an exploratory action, the robot was controlled to raise its end-effector for 30 s such that the temperature sensors could be restored to the ambient temperature.

We evaluated the performance of our proposed method based on a test dataset built by the robot by applying each actions 20 times on each object. During this process, objects were manually shifted and rotated so that the data was robust against the variations in the object contact locations with the artificial skin.

We first evaluated the performance of our proposed robotic multiple feature observation combination algorithm. To do this, the robot selected 10 groups of objects (shown in Fig. 1) to construct the GPC observation models for each of the seven exploratory actions. Each group contained five objects that were selected randomly from the old and new object lists, following a uniform distribution. The algorithm performance was evaluated by the discrimination accuracy of the test dataset predicted by the GPC models with the growing number of feature observations. We compared our method with the baseline methods that built the GPC models using only a single sensor modality.

The experiments were conducted 10 times for each object group. For a fair comparison, we used RBF kernel [28] for each sensor modality. Results are plotted in Fig. 6. For all seven exploratory actions, our proposed algorithm either took advantage of combining different sensor modalities to reach the best discrimination accuracy ($P1$, $P2$, $C1$, $S4$ in Fig. 6), or performed the same as the best single-sensor result ($S1$, $S2$, $S3$ in Fig. 6), indicating that the robot actively selected the most informative sensory feedback to learn about objects.

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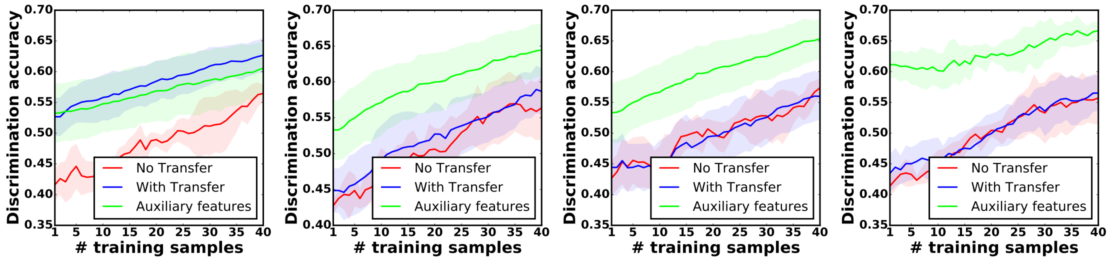

(a) 5 old objects (b) 7 old objects (c) 10 old objects (d) Feature augmentation

Figure 9. Increasing the number of old objects from 3, 5, 7 to 10, and comparing the performance of different learning methods. Red: baseline method; Blue: APTKT without auxiliary features; Green: APTKT with auxiliary features.

5.3. Evaluation of the Transfer Learning Method with Different Groups of Prior Objects

In this experiment, we evaluated the performance of APTKT with different groups of prior objects. To start the learning process, the robot applied each of the seven actions once on each new object. When the robot iteratively learned the new objects' physical properties, it updated both the multiple feature observations combination and the prior tactile knowledge built by the dependent GPC models with all the feature observations collected so far. At each learning iteration, we measured the object discrimination accuracy of the test dataset. The transfer learning performance was compared with the learning process without prior knowledge as the baseline method.

We randomly shuffled the prior objects into ten groups. Each group consisted of the feature observations and the observation models from three prior objects. We conducted the experiment with five trials for each group. In each trial, the robot followed the transfer learning approach and no-transfer approach to collect 40 feature observations in total, allowing a fair comparison between different learning strategies to be made. Fig. 7 illustrates that with the help of prior knowledge, the robot consistently outperformed the learning process without prior knowledge with a discrimination accuracy of 10%. In order to further evaluate the robustness of APTKT, the robot was tasked to learn about objects via applying only *one* of the exploratory actions. The experimental procedure was the same as the one described above. The results are shown in Fig. 8. As can be seen, by actions P1, P2 and C1, The robot had a larger improvement than actions S1, S2, S3 and S4. For example, the robot increased the discrimination accuracy by 25%, when it reused the prior tactile instance knowledge from the movement P2. However, when learning about objects by actions S1 and S4, little improvement was seen. This was due to the fact that different exploratory actions produced different object feature observations. For action P2, there existed higher related prior tactile knowledge than S1 and S4, and the robot could benefit more on it.

In all scenarios, using our proposed transfer learning algorithm, the robot could achieve a higher discrimination accuracy than the baseline method with the same number of feature observations. Therefore, we can conclude that APTKT helps the robot build reliable observation models of new objects with fewer training samples, even when only one kind of the exploratory action is applied.

5.4. Increasing the Number of Prior Objects

We further evaluated the performance of our proposed method with an increasing number of prior tactile experiences. Intuitively, as the number of old objects grows, it is more likely that the robot can find highly-related prior tactile knowledge, so that the learning performance can continue to be improved. In this regard, following the same procedure described above, we increased the number of old objects from 5, 7 to 10 and conducted each experiment five trials. Unexpectedly, as Fig. 9(b), Fig. 9(c) and Fig. 9(d) shows, the growing number of prior tactile knowledge reduced the transfer

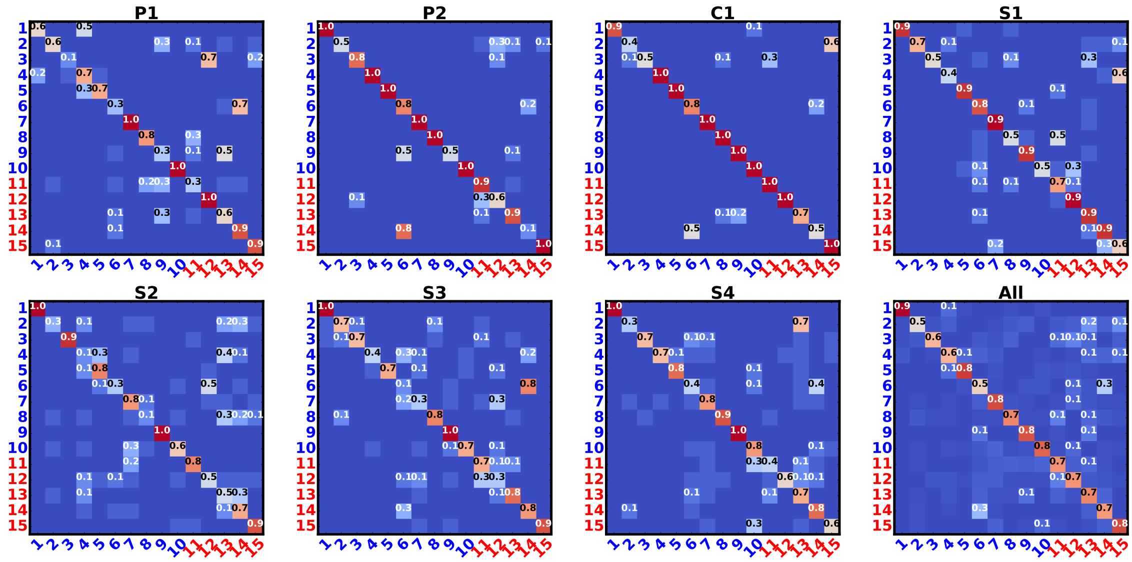

Figure 10. object confusion matrices (value normalized between 0 and 1) for each exploratory action and the average. The blue indices represent the old objects. The red indices represent the new objects, with #11 - #15 indicating new objects #1 - #5. Best viewed in magnification.

learning improvement. This was because the object relatedness ρ predicted by the old object GPC models was underestimated, when there existed many old objects.

To compensate for this, we proposed using a feature augmentation trick that ulitized the predictions as auxiliary features to describe the physical properties of the objects. We defined $p(c_i^{\text{old}}|\mathbf{v})$ as the prediction probability that a feature observation from the new object $\mathbf{v}$ is assigned to the old object c_i^{old}. Then we augmented a feature observation $\mathbf{v}$ from a new object as:

$$\mathbf{v}' = [\underbrace{\mathbf{v},}_{\text{original features}} \quad \underbrace{p(c_1^{\text{old}}|\mathbf{v}), ..., p(c_i^{\text{old}}|\mathbf{v}), ..., p(o_{N_{\text{old}}}^{\text{old}}|\mathbf{x})}_{\text{predictions from old objects' observation models}}]. \tag{4}$$

The auxiliary features $[p(c_1^{\text{old}}|\mathbf{x}), ..., p(c_{N_{\text{old}}}^{\text{old}}|\mathbf{x})]$ can be regarded to be perceived from an auxiliary sensor. Therefore, we directly employed our proposed multiple feature observation combination method to the augmented feature observations by casting a weight to its kernel. The augmented feature observations were then used to build the new object dependent GPC models.

We tested our proposed feature augmentation technique when the robot leveraged 3, 5, 7, and 10 prior objects' prior tactile knowledge to learn about new objects via all seven actions. The learning performance is shown by the green curves in Fig. 9(a) - Fig. 9(d). Clearly, by introducing the probability predictions as auxiliary features, the robot was able to reuse the prior tactile knowledge again, and achieved similar improvement of discrimination accuracy for 3 prior objects, and higher improvement for 5, 7, and 10 prior objects compared to the other methods. Specifically, when resuing 10 prior objects, the robot achieved 20% higher discrimination accuracy than the baseline method, when only *one* new feature observation was collected, showing the one-shot learning behaviour. This experiment also indicates that with a further growing number of prior objects, a further improvement of discrimination accuracy is achievable.

5.5. Negative Prior Tactile Knowledge Transfer Testing

When the constructed prior tactile exploratory action experiences are not relevant to the new objects, a brute-force transfer may degrade the learning performance, resulting in the negative

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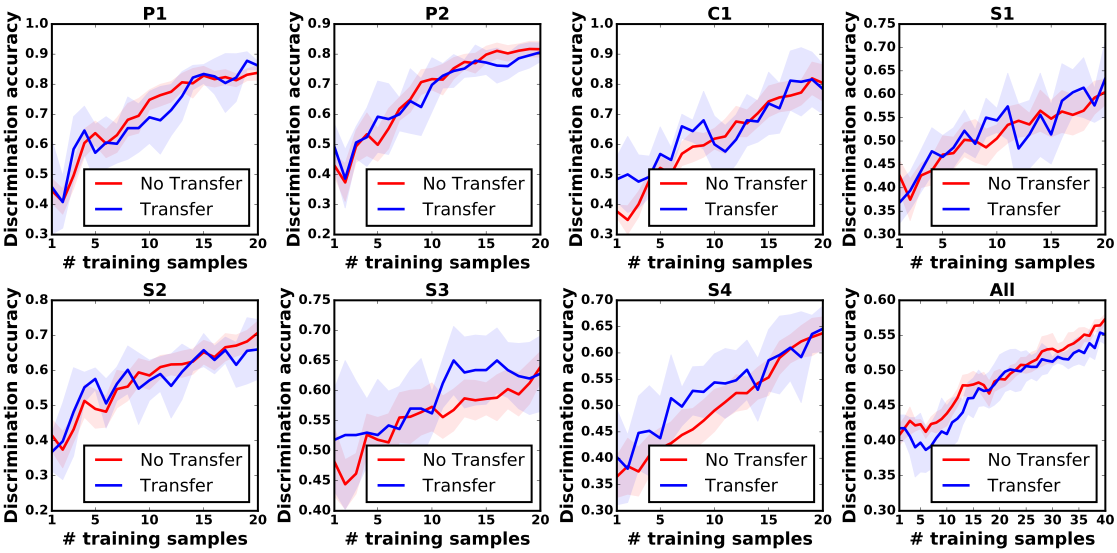

Figure 11. Negative prior tactile knowledge transfer testing. The prior objects were deliberately selected that were unrelated to the new objects.

knowledge transfer phenomena. In this case, the transfer learning algorithm should stop leveraging irrelevant prior knowledge.

In order to evaluate APTKT against the negative tactile knowledge transfer, we deliberately selected irrelevant prior objects and compared the transfer learning performance with the baseline method, following the same experiment process described in Sec. 5.3. When finding which objects were relevant (or irrelevant) to each other, we built object confusion matrices to roughly evaluate the object similarity. To do this, for each of the seven exploratory actions, we trained a Gaussian Mixture Model (GMM) and calculated the object confusion matrix. We further calculated the confusion matrix averaged over all exploratory actions. The results are shown in Fig. 10. According to Fig. 10, objects {1, 5, 7} were dissimilar to the new objects (objects {11 - 15}) regarding the exploratory movement P1, objects {1, 4, 7} for P2, objects {4, 7, 10} for C1, objects {1, 6, 9} for S1, objects {1, 7, 10} for S2, objects {1, 3, 9} for S3, and objects {1, 3, 8} for S4. We thus used these objects as prior objects to test the transfer learning performance via the single exploratory action. We further selected objects {1, 5, 10} to test the learning process via all exploratory actions, since these three objects shared relative small similarity to the new objects.

The results in Fig. 11 illustrate that the discrimination accuracy achieved by APTKT was similar to the baseline method, when the robot applied either one or all seven exploratory actions. The results indicate that our proposed algorithm stopped transferring negative prior tactile instance knowledge.

6. Conclusions

In this work, we proposed a transfer learning method for a robot equipped with multi-modal artificial skin to actively reuse the prior tactile exploratory action experiences when learning about the detailed physical properties of new objects. These prior action experiences are built by the feature observations, when a robotic arm equipped with a multi-modal artificial skin applies the pressing, sliding and static contact movements with different action parameters on objects. The feature observations are perceived from multiple sensory modalities. Using our proposed tactile transfer learning method, the robot has a “warm start" of the learning process. It applies fewer exploratory actions and gains a more precise tactile knowledge of new objects.

In the future, we will extend our method to more exploratory actions (such as tapping and lifting), so that the robot can transfer more exploratory action experiences to learn more physical properties of an object, such as auditory feedback and center of mass. Furthermore, it would be an interesting topic to research how to transfer the prior tactile knowledge across different exploratory actions, e.g. transferring the tactile knowledge from pressing to static contact movement.

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