Active Tactile Transfer Learning for Object Discrimination in an Unstructured Environment using Multimodal Robotic Skin

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In this paper, we propose a probabilistic active tactile transfer learning (ATTL) method to enable robotic systems to exploit their prior tactile knowledge while discriminating among objects via their physical properties (surface texture, stiffness, and thermal conductivity). Using the proposed method, the robot autonomously selects and exploits its most relevant prior tactile knowledge to efficiently learn about new unknown objects with a few training samples or even one. The experimental results show that using our proposed method, the robot successfully discriminated among new objects with 72% discrimination accuracy using only one training sample (on-shot-tactile-learning). Furthermore, the results demonstrate that our method is robust against transferring irrelevant prior tactile knowledge (negative tactile knowledge transfer).

Keywords: Active tactile exploration, active tactile transfer learning, active workspace exploration, pre-touch, tactile sensing, multimodal robotic skin.

1. Introduction

Touch is perhaps the most overlooked sense. Every one of us receives tactile information about the world around us every second of the day,1 including grasping and manipulation,2 assessing object properties,3 determining the underlying emotion associated with a touch gesture.4 It is difficult to compensate for a lack of touch through other senses. What happens if we have all sense modalities other than the
tactile sensing? Consider a scenario of touching objects after keeping hands on an ice block for a while.

Westling et al. conducted an experiment by anesthetizing the skin of the hand from human subjects. In this way, the mechanoreceptors which are specialized nerve endings for responding mechanical stimulations were no longer available to the brain. In this case, the subjects could not grasp the experimental objects as the hand and fingers movements become inaccurate and unstable.

For robotic systems that interact with dynamic environments, it is important to recognize objects via their physical properties (such as surface texture, stiffness, center of mass, and thermal conductivity). This is difficult to achieve even with advanced vision techniques, due to poor lighting and occlusion. As an alternative, tactile sensing can provide rich information to the robots from different contact points.

We humans use our sense of touch to actively explore our environment and objects based on various physical properties. In this regard, we strategically select exploratory actions to perceive physical properties of the objects (e.g. sliding to sense the textural properties, pressing to estimate the stiffness, and static contact to measure the thermal conductivity). Active tactile exploration is a complex procedure which requires efficient perception and a learning methods. Moreover, we intelligently re-use our previously acquired tactile knowledge to actively learn about new objects. Our prior tactile knowledge, or past tactile experience, helps us to efficiently explore new objects by performing fewer active exploratory actions or even one. In other words, we learn about new objects with fewer training samples or even one (one-shot learning) while re-using our prior knowledge. In order to facilitate this ability in the robotic system, in this study we propose an active tactile transfer learning method so that the robot with a sense of touch can efficiently learn about objects via their physical properties by exploiting the prior tactile knowledge.

1.1. Related work

Haptically accessible object characteristics can be divided into three general classes: geometric information, material properties, and inner properties (e.g. center of mass). Robots can recognize the geometric properties of objects by perceiving their shapes via either proprioceptive receptors or cutaneous receptors, by exhaustively touching a single object with a known orientation and location in the workspace. The object material can be characterized and identified by its textural properties, stiffness, and thermal conductivity. The robot can sense the textural properties of objects using cutaneous tactile receptors by moving fingertips on the objects' surfaces. The stiffness of objects can also be measured by pressing the robot fingertips against the objects. Likewise, the thermal conductivity can be perceived by building light contact with the objects' surfaces.

Previous researchers have used various robotic systems and tactile sensors to passively explore objects and discriminate among them. They used a predefined
number of exploratory actions to sense the physical properties of objects with fixed positions and orientation in a known workspace.

On the contrary, active tactile exploration has shown great potential for enabling the robotic system with more natural and human-like strategies. An autonomous robot should be able to select and execute the exploratory actions that provide it with the maximum amount of information. In this regard, several approaches were proposed to actively discriminate among objects using their physical properties. For example, Lepora et al. controlled a biomimetic fingertip to slide along ten different surfaces to perceive their textural properties. In order to actively discriminate among the surfaces under position uncertainty, the authors constructed the observation models for the textures and the positions of the surfaces offline, by uniformly sampling the collected training data of each surface texture and each possible surface position under a range of contact depths. In another study, the Weiss Robotics sensor was mounted on the end-effector of a robot arm to classify 21 objects. To do this, the authors created a database of tactile observations offline by grasping each object with a pre-designed trajectory. The authors managed to actively recognize objects using tactile images, which were produced by strategically selecting the height of the robot finger and grasping the objects. Matrins et al. aimed at developing a general active haptic exploration and recognition strategy for heterogeneous surfaces. The experiments were conducted to search and follow the discontinuities between regions of surfaces with two different materials. Xu et al. used the index finger of the Shadow Hand with the BioTac sensor to collect training data by executing three different exploratory actions (pressing for stiffness, sliding for surface texture, and static contact for thermal conductivity) five times on each experimental object. However, the experiments were only carried out in the simulation using uniformly collected data offline. Tanaka et al. combined Gaussian process latent variable and nonlinear dimensionality reduction method to actively discriminate among four cups in the real experiments. The authors collected 400 training samples uniformly using three fingers of the Shadow hand, which was fixed and the objects were placed on a turntable. The observation model was constructed with action features using the index finger with 2-DOF to generate inceptive and horizontal movements on the objects. Since the proposed method requires a huge amount of training data, the high dimensional action space makes the optimal action search and model learning intractable. The informativeness of the training data collected from each object is different. Some objects have distinctive tactile properties, which makes them easy to be discriminated. Therefore, collecting too many training samples by applying exploratory actions is redundant; whereas for objects, whose physical properties are similar and thus can be easily confused with other objects’ properties, it is necessary to collect sufficient samples to construct reliable and robust observation models. However, In the above-mentioned works, the training samples were collected uniformly and offline to construct the observation models.

In our previous study, we proposed an active tactile learning method to enable
the robotic system to efficiently learn about unknown objects via their physical properties by selecting strategically the next object and the next exploratory action. However, the robot is still unable to exploit its prior tactile knowledge when it learns a new set of unknown objects. In the robotic learning problem, collecting training samples is time and memory consuming. In addition, there may not always be sufficient training data available. To tackle with this problem, the robot can reuse its previously obtained prior knowledge when it learns new objects with fewer training samples or even one (tactile transfer learning).

Although there are many research studies proposing various transfer learning strategies in visual categorization, reinforcement learning, data mining, brain computer interface, and deep learning, to the best of our knowledge, in the tactile learning domain, it is only our previous work which proposed a tactile transfer learning method for object texture discrimination (Kaboli et al.[55, 56]). In our previous work, a robotic hand re-used its learned texture models from the prior objects to discriminate among new in-hand objects via their textural properties with a few training samples or even one. The robotic hand slid its fingers to passively perceive the textural properties of each object at each time and the training samples were collected uniformly across all objects.

1.2. Contribution

In this study, for the first time in the field of tactile learning, we propose a probabilistic tactile-based active transfer learning method to enable robotic systems with the sense of touch to be one step closer to human-like tactile exploration and learning strategy. Using our proposed algorithm, the robot autonomously selects and exploits the most relevant obtained prior tactile knowledge (past tactile experience) to learn about new objects via their physical properties (surface textures, stiffness, and thermal conductivity) with a few tactile exploratory actions (sliding, pressing, and static contact) or a low number of training samples. Our proposed active tactile transfer learning algorithm (ATTL) is demonstrated in Fig. 2.

2. System Description

2.1. Artificial Robotic Skin

In order to emulate a human sense of touch, we have designed and manufactured multi-modal tactile sensors to provide robotic systems with the ability of pre-touch and sense of touch. Each skin cell has one micro controller and a set of multi-modal tactile sensors, including one proximity sensor, one three-axis accelerometer, one temperature sensor, and three normal-force sensors, (see Table 1). All skin cells are directly connected with each other via bendable and stretchable inter-connectors.
Fig. 1. The scenario of active tactile transfer learning for object discrimination in the unstructured environment. The robotic arm (A) equipped with multimodal artificial skin (B) can actively learn about prior objects via surface texture, stiffness, and thermal conductivity (C) in an unstructured environment in order to build the tactile knowledge of these objects. Then the robot can leverage its obtained prior tactile knowledge (D) to actively learn about new objects (E).

Table 1. The multi-modal robotic skin characteristics.

<table>
<thead>
<tr>
<th>Modality</th>
<th>Acceleration</th>
<th>Force</th>
<th>Proximity</th>
<th>Temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor</td>
<td>BMA250</td>
<td>Customized</td>
<td>VCNL4010</td>
<td>LM71</td>
</tr>
<tr>
<td>Per Cell</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Range</td>
<td>±2 g</td>
<td>&gt; 0 - 10 N</td>
<td>1 - 200 mm</td>
<td>-40 - 150°C</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>0 - 1 kHz</td>
<td>0 - 33 kHz</td>
<td>0 - 250 Hz</td>
<td>0 - 7 Hz</td>
</tr>
</tbody>
</table>

2.2. Robot

We mounted one skin patch on the end-effector of a 6-DoF industrial robot called UR10 (Universal Robots). The skin patch consists of 7 skin cells that include: 7 proximity sensors, 7 three-axis accelerometer sensors, 7 temperature sensors, and 21 normal-force sensors (see Fig. 1 (A,B)).
3. Tactile-based Object Exploration in an Unknown Workspace

3.1. Workspace Exploration

In order to perceive the physical properties of the objects in an unknown workspace, the robot should be able to autonomously explore the workspace and localize the objects therein. In this study, we use our previously proposed active pre-touch strategy for the workspace exploration.37 By using our proposed active pre-touch method, the robot autonomously finds the number of objects in the workspace, estimates their positions and orientations, and computes their geometric centroids.

3.2. Objects’ Physical Properties Perception

A robotic system with the sense of touch needs to execute various exploratory actions on the objects to perceive their physical properties, as we humans do. For instance, a robot presses on an object to measure its stiffness, slides its sensitive area on the object’s surface to sense its textural property, and performs a static contact to estimate the thermal conductivity of the object.
3.2.1. **Stiffness Estimation**

In order to measure the stiffness of an object, the UR10 robotic arm with an artificial skin on its end-effector first establishes a light contact with the objects (see Fig. 3). The light contact is detected as soon as the measured normal force averaged over all sensors \( F_{av} = \frac{1}{N_c N_r} \sum_{n_c=1}^{N_c} \sum_{n_r=1}^{N_r} F_{n_c n_r} \) exceeds a threshold \( f_t \), i.e. \( F_{av} > f_t \). (\( N_c = 7 \) is the number of skin cell and \( N_r = 3 \) is the number of normal force sensors in each skin cell). Then, the robot presses the top surface of the object by its end-effector. For all normal force sensors \( F_{n_c n_r} \), the difference between the forces recorded before and after pressing \( \Delta F_{n_c n_r} \) is used as an indication of the stiffness on the local contact area. The averaged difference value over all force sensors serves as a measurement of the object stiffness \( \frac{1}{N_c N_r} \sum_{n_c=1}^{N_c} \sum_{n_r=1}^{N_r} \Delta F_{n_c n_r} \).

3.2.2. **Textural Properties’ Perception**

To sense the textural properties of objects, the robot slides its end-effector with multimodal artificial skin across the surface of objects. The sliding action generates vibro-tactile signals which are measured by the three-axis accelerometer in each skin cell \( (a_{nx}^x, a_{ny}^y, a_{nz}^z) \). To extract the robust tactile information, we used our previously proposed tactile feature descriptors.\(^{57-59}\) Our proposed feature descriptors represent the statistical properties of the tactile signals in the time domains (see Table 2). \( A(s_n) \) is the total power of a signal. \( M(s_n) \) is the square root of the ratio of the variance of the first derivative of the signal to that of the signal. \( C(s_n) \) is the second derivative of the variance and shows how the shape of the signal is similar to a pure sine wave. \( L(s_n, v_n) \) is the linear correlations between each axis of the accelerometer. The proposed descriptors for \( N_c \) number of skin cells are defined as \( A_{total}, M_{total}, \) and \( C_{total} \), and \( L_{total} \) in Table 2. In all the equations, \( s_n \) and \( v_n \) are measured tactile signals. The final tactile descriptor \( D_{total} \) is the concatenation of all computed tactile features and can be defined as: \( D_{total} = [A_{total}; M_{total}; C_{total}; L_{total}] \).
Let us consider a scenario in which the robotic system has already learned \( N_{\text{prior}} \) number of objects \( O_{\text{prior}} = \{ o_{j}^{\text{prior}} \}_{j=1}^{N_{\text{prior}}} \) via their physical properties (stiffness, surface texture, and thermal conductivity, denoted as \( S = \{ s_{1}, s_{2}, s_{3} \} \)). The captured prior tactile knowledge consists of the prior objects’ feature observations \( Z_{\text{prior}} = \{ Z_{s_{1}}^{\text{prior}}, Z_{s_{2}}^{\text{prior}}, Z_{s_{3}}^{\text{prior}} \} \) and their constructed reliable observation models denoted by \( Z_{\text{prior}} \xrightarrow{\text{prior}} O_{\text{prior}} \) (see Fig. 1 (C) and (D)).
Here, the task of the robot is to learn about a new set of objects (Fig. 1 (E)) via their physical properties. We denote $N_{\text{new}}$, number of new objects as $O_{\text{new}} = \{o_{\text{new}}^i\}_{i=1}^{N_{\text{new}}}$. Some of the new objects might share similar physical properties with the prior objects (for instance similar textural properties). Now, the robot is asked to actively learn about the new objects properties while re-using its past tactile experience. In other words, the robotic should efficiently construct the observation models $Z_{\text{new}} \xrightarrow{\text{new}} O_{\text{new}}$, with the feature observations $Z_{\text{new}} = \{Z_{s1}^{\text{new}}, Z_{s2}^{\text{new}}, Z_{s3}^{\text{new}}\}$ for each of the physical properties perceived during the exploration of the new objects, while re-using the obtained tactile knowledge of the prior objects.

We formulate the ATTL as a standard supervised learning problem for multi-class classification, where each object is regarded as a class $o$; for each tactile property $s$, a Gaussian Process Classification (GPC) is used to construct the objects’ observation models. GPC describes the function $X \xrightarrow{s} Y$, where $X$ is the observation set and $Y$ is the target set which contains integers indicating the labels of the input data. The model assumes that there is an underlying latent function $X \xrightarrow{\text{GP}} \mathbb{R}$, which is sampled by the GP prior:

$$g \sim \mathcal{G}(\mathbf{0}, K(X, X))$$

with zero mean and kernel function $K : X \times X \rightarrow \mathbb{R}$. The kernel function describes the similarity between two observations. In our work, one-vs-all multiclass GPC is employed. For each object, a binary GPC ($f_n(\cdot)$) is learned, with its hyper-parameters being optimized through maximizing the log likelihood. Given a new sample $x^*$, each binary classifier predicts the observation probability of its label $p(y_n|x^*)$. The sample is assigned to the class with the largest predicted probability:

$$y^* = \arg \max_{y_n \in Y} p(y_n|x^*). \quad (1)$$

### 4.2. Methodology

Our ATTL algorithm method has three main steps:

(I) The robot first executes each of the exploratory actions (sliding, pressing, and static contact) once on each new object to collect a small number of new objects’ feature observations $Z_{\text{new}}$ (one-time data collection).

(II) For each new object and each physical property, the robot transfers the prior tactile knowledge consisting of the observation models $f_{\text{prior}}(\cdot)$ and feature observations $Z_{\text{prior}}$. To do this, the robot first selects the most relevant prior knowledge, in our case, feature observations to transfer (Sec. 4.2.1). Then, it exploits the selected feature observations and the predictions from the prior objects’ observation models to improve the new objects’ GPC models (Sec. 4.2.2).

(III) The robot iteratively constructs the new objects’ observation models. In each iteration, the robot actively selects the next object and next physical property to explore and collects the new objects’ feature observations (Sec. 4.2.3). Then, it updates its prior tactile knowledge regarding only the selected physical property, including re-selecting the prior tactile knowledge and transferring it to the new objects (Sec. 4.2.1 and Sec. 4.2.2). The learning process is repeated until there is
no improvement in the uncertainty of the new objects’ observation models. Our algorithm is demonstrated by Algorithm 1. In the rest of this paper, we refer to \( j \) as the prior object \( o_{j}^{\text{prior}} \), and \( i \) as the new object \( o_{i}^{\text{new}} \).

4.2.1. Prior Tactile Knowledge Selection

When learning about a new object via one physical property, the ATTL selects the most relevant prior object to transfer (from where to transfer), taking advantage of the prediction from the observation models constructed by the prior objects. More formally, consider \( p(o_{j}^{\text{prior}}|v_{i}^{\text{new}}) \) to be as a prediction from the prior object’s \((o_{j}^{\text{prior}})\) observation model with regard to the physical property \( s \). Here, \( v_{i}^{\text{new}} \) is a feature observation from the new object \( o_{i}^{\text{new}} \). We calculate the average prediction to all \( N_{i}^{\text{new}} \) number of samples that belong to the new object \( o_{i}^{\text{new}} \) by \( \bar{p}(o_{j}^{\text{prior}}|Z_{s,i}^{\text{new}}) = \frac{1}{N_{i}^{\text{new}}} \sum p(o_{j}^{\text{prior}}|v_{i}^{\text{new}}) \). This value estimates the relatedness of the physical property \( s \) between the prior object \( o_{j}^{\text{prior}} \) and the new object \( o_{i}^{\text{new}} \). The higher the value is, the more similar two objects are. Thus, the prior object with the largest average prediction value (denoted as \( o_{j}^{\text{prior}^*} \)) can be selected to transfer its feature observations of the physical property \( s \) to the new objects:

\[
o_{j}^{\text{prior}^*} = \arg \max_{o_{j}^{\text{prior}} \in O_{\text{prior}}} \bar{p}(o_{j}^{\text{prior}}|Z_{s,i}^{\text{new}}),
\]

(2)

4.2.2. Prior Tactile Knowledge Transfer

We described in Sec. 4.2.1 “from where” the robot transfers the prior objects’ feature observations. Here, we explain “how and how much” the robot reuses its prior knowledge. While leveraging the prior object’s \((o_{j}^{\text{prior}})\) feature observations \( Z_{s,j}^{\text{prior}} \) of the physical property “\( s \)” to the new object \( o_{i}^{\text{new}} \), we define \( g_{s,j}^{\text{prior}} \) and \( g_{s,i}^{\text{new}} \) to be the latent functions of the GPC models constructed by the feature observations from prior objects \( Z_{s,j}^{\text{prior}} \) and new object \( Z_{s,i}^{\text{new}} \) respectively. It is assumed that these two functions are not independent from each other, but are sampled dependently over a Gaussian prior (hybrid GP). We use this hybrid GP as the observation model of the new object:

\[
g_{s,i}^{\text{new}} \leftarrow [g_{s,j}^{\text{prior}}; g_{s,i}^{\text{new}}],
\]

(3)

the kernel function can be defined as:

\[
K = \begin{pmatrix}
K_{z}(Z_{s,j}^{\text{prior}}, Z_{s,j}^{\text{prior}}) & \gamma K_{z}(Z_{s,i}^{\text{new}}, Z_{s,j}^{\text{prior}}) \\
\gamma K_{z}(Z_{s,j}^{\text{prior}}, Z_{s,j}^{\text{prior}}) & K_{z}(Z_{s,i}^{\text{new}}, Z_{s,i}^{\text{new}})
\end{pmatrix}.
\]

(4)
where $K_z$ is the base kernel function that measures the similarity of training samples. In our case, we use radial basis function (RBF) whose hyper-parameters are found by maximizing the log-likelihood of this hybrid GPC model.

In Eq. 4, $K_z(Z_{j,prior}^i, Z_{j,prior}^i)$ and $K_z(Z_{new}^i, Z_{new}^i)$ measure the similarity for feature observations of the prior object and the new object respectively. And $\gamma K_z(Z_{j,prior}^i, Z_{new}^i)$ and $\gamma K_z(Z_{new}^i, Z_{j,prior}^i)$ measure the similarity between the feature observations of the prior object and the new object respectively. The parameter $\gamma$ ranges between 0 and 1. As analyzed by Chai et al., $\gamma$ controls “how much” the feature observations should be transferred. $\gamma = 0$ indicates that the prior object and the new object are irrelevant, whereas $\gamma = 1$ indicates that the two objects are regarded to be the same. We estimate $\gamma$ by the average prediction probability of the training samples:

$$\gamma = \begin{cases} \hat{p}(o_{j,prior}^i | Z_{new}^i) & \text{if } \hat{p}(o_{j,prior}^i | Z_{new}^i) > \epsilon, \\ 0 & \text{otherwise.} \end{cases}$$

with $\epsilon$ being the threshold below which a transfer of irrelevant prior tactile knowledge is avoided.

The method introduced above uses the hybrid GP to transfer the prior tactile knowledge. The parameter $\gamma$ controls “how much” to transfer. It can also stop transferring irrelevant prior tactile information. However, it does not fully exploit the tactile knowledge from all prior objects, since it combines the feature observations of one prior object to each new object. In this regard, we use a feature augmentation strategy. The prediction outputs from all prior objects’ observation models are employed as auxiliary features. The augmented representation of a new sample $v$ can be defined as:

$$v' = \left[ v; p(o_{j,prior}^1 | v); p(o_{j,prior}^2 | v); \ldots; p(o_{j,prior}^N | v) \right].$$

The augmented feature observations are then used to train the hybrid GPC in Eq. 3.

### 4.2.3. Next New Object and Physical Property Selection

When the robot iteratively updates the new objects’ observation models, it actively decides which new object to explore and which physical property to perceive in order to collect new feature observations. Here, we use our previously proposed active touch for learning objects’ physical properties method (AT-PPL). Our method estimates the classification competence of the new objects’ observation models which guides the robot to the next round of data collection.
Algorithm 1: The Proposed Active Tactile Transfer Learning (ATTL)

Input: \( O_{new} = \{ o_{i,new} \}_{i=1}^{N_{new}}, \ L_{new} = \{ l_{i,new} \}_{i=1}^{N_{new}} \) \( N_{new} \) new objects with positions \( L_{new} \), each object is regarded as a class \( o_{i,new} \).

\( O_{prior} = \{ o_{j,prior} \}_{j=1}^{N_{prior}}, \ Z_{prior}, \ Z_{prior} \) \( N_{prior} \) Prior knowledge

Output: \( Z_{new}^{n_{new}}, Z_{new}^{n_{new}} \) \( N_{new} \) New objects’ GPCs and feature observations.

Initialization: \( Z_{new}^{n_{new}} \) \( N_{new} \) One time data collection for the new objects.

Prior tactile knowledge transfer for all new objects & physical properties for \( s = \{ s_1, s_2, s_3 \} \) do

\begin{align*}
    \text{for } i = 1 : N_{new} \text{ do} \\
    & o_{s, i}^{prior} \leftarrow \text{priorKnowledgeSelection}(p(o_{s, i}^{prior} | Z_{s, i}^{new})) \quad \triangleright \text{Sec. 4.2.1} \\
    & \gamma_{s, i} \leftarrow \text{correlationEstimate}(o_{s, i}^{prior}, p(o_{s, i}^{prior} | Z_{s, i}^{new})) \quad \triangleright \text{Eq. 5} \\
    & Z_{s, i}^{new'} \leftarrow \text{featureAugmentation}(Z_{s, i}^{new}) \quad \triangleright \text{Eq. 6} \\
    & f_{s, i}(\cdot) \leftarrow \text{updateGPC}(Z_{s, i}^{new'}, \gamma_{s, i}) \quad \triangleright \text{Sec. 4.2.2} \\
    \end{align*}

end

\( Z_{new}^{n_{new}} = \{ Z_{s_1, i}^{new}, Z_{s_2, i}^{new}, Z_{s_3, i}^{new} \}_{i=1}^{N_{new}} \)

\( f_{new}(\cdot) = \{ f_{s_1}(\cdot), f_{s_2}(\cdot), f_{s_3}(\cdot) \}_{i=1}^{N_{new}} \)

while not stop condition() do

New Feature Observation Collection

\( A(s, o_{i,new}^{n_{new}}) \leftarrow \text{competenceEstimation}(f_{new}(\cdot)) \quad \triangleright \text{Eq. 8} \\
\lambda(s^*, o_{i,new}^{n_{new}}) \leftarrow \text{objectPropertySelection}(A(s, o_{i,new}^{n_{new}})) \quad \triangleright \text{Eq. 9} \\
\text{moveTo}(l_{new}) \quad \triangleright \text{Robot moves to the object} \\
\text{v}_{new} \leftarrow \text{actionExecution}(s^*) \quad \triangleright \text{Get new training sample} \\
\text{Z}_{new} \leftarrow \text{Z}_{new} \cup \text{v}_{new} \quad \triangleright \text{Update training database}

Update prior tactile knowledge for \( i = 1 : N_{new} \) do

\begin{align*}
    \text{for } i = 1 : N_{new} \text{ do} \\
    & o_{s^*, i}^{prior} \leftarrow \text{priorKnowledgeSelection}(p(o_{s^*, i}^{prior} | Z_{s^*, i}^{new})) ; \\
    & \gamma_{s^*, i} \leftarrow \text{correlationEstimate}(o_{s^*, i}^{prior}, p(o_{s^*, i}^{prior} | Z_{s^*, i}^{new})) \\
    & Z_{s^*, i}^{new'} \leftarrow \text{featureAugmentation}(Z_{s^*, i}^{new}) \\
    & f_{s^*, i}(\cdot) \leftarrow \text{updateGPC}(Z_{s^*, i}^{new'}, \gamma_{s^*, i}) \\
    \end{align*}

end

end

First, the robot measures the Shannon entropy of each new objects’ feature observation that has been collected \( \text{v}_{new} \in Z_{new}^{n_{new}}: \)

\[ H(\text{v}_{new}) = - \sum_{o_{i,new}^{n_{new}} \in O_{new}} p(o_{i,new}^{n_{new}} | \text{v}_{new}) \log(p(o_{i,new}^{n_{new}} | \text{v}_{new})). \]
Then the training data set $Z^{\text{new}}$ is divided into categories according to the physical property $s$ and object class $o_i^{\text{new}}$. The GPC’s classification competence $A(s, o_i^{\text{new}})$ is estimated as the mean value of the Shannon entropy:

$$A(s, o_i^{\text{new}}) = \frac{1}{N_{s,i}^{\text{new}}} \sum_{v^{\text{new}} \in Z_{s,i}^{\text{new}}} H(v^{\text{new}}),$$

where $N_{s,i}^{\text{new}}$ is the number of feature observations from $Z_{s,i}^{\text{new}}$. The higher $A(s, o_i^{\text{new}})$ is, the more uncertain the robot is about the object.

We define $A(s, o_i^{\text{new}})$ as a function of the object $o_i^{\text{new}}$ and physical property $s$. After selecting $A(s, o_i^{\text{new}})$, the robot moves to the object $o_i^{\text{new}}$ and executes the corresponding exploratory action to perceive the physical property $s$. In order to efficiently collect new feature observations, the ATL algorithm determines the next object $o^{\text{new}^*}$ and next physical property $s^*$ by:

$$\lambda(s^*, o^{\text{new}^*}) = \begin{cases} \arg \max_{s \in \{s_1, s_2, s_3\}, o^{\text{new}^*} \in G^{\text{new}^*}} A(s, o_i^{\text{new}}), & \text{if } p_\lambda > \epsilon_\lambda, \\ s^* = \mathcal{U}\{s_1, s_2, s_3\}, o^{\text{new}^*} = \mathcal{U}\{o_1^{\text{new}}, \ldots, o_{N_{s,i}^{\text{new}}}^{\text{new}}\}, & \text{otherwise}. \end{cases}$$

where $\epsilon_\lambda$ is the parameter to control the exploration-exploitation trade-off. $p_\lambda$ is a probability which is uniformly generated with $\mathcal{U}(0, 1)$ at each learning iteration.

5. Experimental Results

5.1. Experimental Objects

In order to assess our proposed ATTL method, we deliberately selected two sets of objects, one set with 21 objects as prior objects (Fig. 4(a)) and another set with 7 objects as new objects (Fig. 4(b)). All experimental objects were made by different materials (such as glass, cardboard, and plastic) with regular and irregular surface textures and various shapes (such as triangular, rectangular, cross, and heart shape). The physical properties of these objects (stiffness, surface textures and thermal conductivity) varied from similar to different.

5.2. Experimental Setting

We assessed the performance of our proposed active tactile transfer learning method (ATTL) in real time. The robot was tasked to actively learn about new objects (Fig. 4(b)) while reusing the prior tactile knowledge constructed from the prior objects (Fig. 4(a)). In each experiment, the workspace was unknown, and the robot had no knowledge about the number of objects and their positions therein. Therefore, before it applied any exploratory actions with objects, the robot used the active pre-touch strategy to explore the unknown workspace and estimate their...
positions and the geometrical centroids. Although the objects had random positions and orientations in the unknown workspace, they were fixed to the table in order not to move when the robot slid its end-effector over their surfaces.

5.3. Workspace Exploration

Fig. 5(a) illustrates the unknown workspace which is a cuboid of $110cm \times 64cm \times 10cm$ (L × W × H). A corresponding Cartesian coordinate frame (world coordinate frame) was defined along its length edge (X-axis), width edge (Y-axis), and height edge (Z-axis). This workspace was discretized into $27 \times 24 \times 10$ grid cells. During the exploration, the sensor array (the end-effector of the robot) was positioned at the maximum height of the workspace and horizontal to the X-Y plane. Fig. 5(b) shows an example of the exploration result. The robot successfully estimated the number and the positions of ten objects that had been randomly placed on the workspace.

5.4. Evaluation of Active Tactile Transfer Learning (ATTL)

5.4.1. Prior Tactile Knowledge Construction

The robot first collected the feature observations from prior objects (Fig. 4(a)), and then constructed observation models via GPC. These feature observations and the constructed models served as the prior tactile knowledge. To do this, the robot
automatically performed each exploratory action 20 times on each of the prior objects. It begun to apply each of the exploratory action with a light contact with each object with approximately 0.05 N. For the pressing movement, the robot first pressed the end-effector 2 mm on the objects’ surface and then recorded the outputs of the normal force sensors for 3 s. To perceive the surface texture of the objects, the robotic slid its artificial skin on the objects with velocity of 1 cm/s for 3 s (in order to collect fair tactile information with all experimental objects). When measuring the thermal conductivity, the robot pressed its sensitive part 2 mm on the objects’ surfaces and held it for 15 s. Then it kept its end-effector up for 30 s so that the temperature sensor recovered to ambient temperature. In this way, the robot could measure the temperature change during the static contact with a similar initial temperature condition.

5.4.2. Test Data Collection for New objects

The performance of the proposed ATTL method was evaluated with a test database of the new objects (Fig. 4(b)). This was achieved by following the same data collection procedure described in Sec. 5.4.1.

5.4.3. Baselines

We compared our proposed ATTL method (with prior tactile knowledge) with the uniform learning method and our previously proposed active tactile learning (ATL) method as baselines. Using the uniform method, the robot uniformly applied each exploratory action on each new object. Using the ATL method, at each learning step the robot can follow our proposed ATL method to strategically select the next object to perceive and the next physical property to explore, however, it was
Fig. 6. Evaluation of the active tactile learning performance using ten prior objects. ATTL is compared with the ATL (no transfer) and uniform (no transfer) methods. The horizontal axis represents the growing number of feature observations, and the vertical axis represents the averaged value of discrimination accuracy on the test data set. (a) Learning about the new objects based on three physical properties. The right small plots show the results from 10 groups of prior objects. Their averaged result is plotted on the left; (b) The learning process based on only stiffness; (c) The learning process based on only surface texture; (d) The learning process based on only thermal conductivity.

unable to exploit its prior tactile knowledge.

5.4.4. Learning about New Objects with Ten Prior Objects

We first evaluated the ATTL performance of learning about new objects with the help of 10 prior objects. This experiment was conducted 10 trials. At each trial, the robot first randomly selected 10 prior objects following the uniform distribution in order to construct a group of prior tactile knowledge. Then the robot reused this tactile knowledge to learn about the new objects by following the ATTL, ATL, and uniform methods five times.

To initialize the learning process, the robot collected one feature observation for each new object and each physical property (stiffness, surface texture, and thermal conductivity). At each step when the robot sampled a new feature observation, the new objects’ discrimination accuracy of the test data set was measured by the new
objects’ observation models, which were re-trained by all the feature observations the robot had collected so far. To have a fair comparison between the ATTL and the baseline methods, the robot collected in total 60 feature observations by exploring the new objects.

Fig. 6(a) illustrates that the ATTL method consistently outperforms the ATL and uniform methods by reaching higher discrimination accuracy when collecting the same number of feature observations. For instance, the robot had in average 20% higher discrimination accuracy than the ATL and uniform strategies, when the robot received only one training sample (one-shot learning) (Fig. 6(a)). By increasing the feature observations from 1 to 60, the robotic system using our proposed ATTL method leveraged the past tactile experience and achieved a discrimination accuracy of 83%, whereas following the ATL and uniform methods, it only obtained 71% and 76%, respectively.

We also evaluated ATTL when the robot used only one of the physical properties (stiffness, surface texture and thermal conductivity) to learn about new objects. In this instance, the total number of feature observations was set to 30. Fig. 6(b), Fig. 6(c) and Fig. 6(d) show that in all three cases, the ATTL outperforms ATL and uniform strategies. Therefore, using our proposed ATTL algorithm, the robot can efficiently construct reliable new objects’ observation models with fewer training samples.

5.4.5. Decreasing the Number of Prior Knowledge
In this experiment, we decreased the number of prior objects from 7, 5 to 3. The robotic system following the same procedure explained above (Sec. 5.4.4) to learn about new objects (Fig. 4(b)). The results in Fig. 7(a), Fig. 7(b), Fig. 7(c), and Fig. 7(d) show that when the robot used fewer prior objects, it achieved lower discrimination accuracy. This is due to the fact that reducing the number of prior objects decreases the probability of finding highly-relevant prior tactile knowledge for the new objects. This phenomena became clearer when we decreased the number of priors objects from 10 to 3. In spite of this, using our ATTL method even with 3 prior objects achieved higher discrimination accuracy than the baseline methods.

5.4.6. Robustness Evaluation of ATTL
So far, the robot was tasked to leverage the prior tactile knowledge constructed by the objects in Fig. 4(a) to learn about objects in Fig. 4(b). To further test the robustness of the ATTL algorithm, in this experiment we randomly selected 7 objects out of all 28 experimental objects as new objects and the rest as prior objects, and conducted the same experiment explained in Sec. 5.4.4 for 50 times. The averaged learning performance was illustrated in Fig. 8. The results clearly show that the robot using the ATTL method with 3 prior objects consistently outperformed the baseline methods with a discrimination accuracy improvement of
5.5. Consistency Evaluation of ATTL for Negative Tactile Knowledge Transfer

In transfer learning, the constructed prior knowledge is not always relevant to new tactile observation models. In this case, a brute-force transfer may even degrade the learning performance, generating a so-called negative knowledge transfer. When the new and the prior objects are not a good match, a transfer learning method should avoid leveraging negative knowledge.

In this experiment, we evaluated our proposed algorithm against the negative tactile knowledge transfer. To do this, we constructed confusion matrices for all
Fig. 8. Learning about new objects with different number of prior objects. The new objects and the prior objects were randomly selected, following the uniform distribution.

28 experimental objects w.r.t each physical property in order to find out which of the prior objects were similar and dissimilar to the new objects. The confusion matrices were constructed by training the Support Vector Machine (SVM) models for all 28 objects with ten training samples randomly selected for each object, and using the trained SVM to predict ten unobserved data instances. We calculated the average confusion between objects and normalized the values between 0 and 100, with 0 being totally dissimilar and 100 highly similar. Fig. 9, Fig. 10, and Fig. 11 demonstrate the resulting confusion matrices constructed for stiffness, texture, and thermal conductivity respectively. The blue index indicates the prior objects, and the red index new objects. Regarding stiffness, the prior objects \{1, 2, 3, 9, 13\} were totally unrelated to the new objects; for surface texture, prior objects \{6, 7, 9, 10, 21\}; and for thermal conductivity, prior objects \{4, 6, 8, 10, 13\}. Therefore, we respectively selected these objects to construct prior tactile knowledge and test ATTL performance, when the robot learned about new objects based on each physical property. We also used objects \{2, 3, 6, 10, 13\} as prior objects for learning based on three properties. The performance of the ATTL method was compared with ATL which served as the baseline. The rest of the procedure was similar to Sec. 5.4.

Fig. 12 illustrates the recognition performance attained using ATTL and ATL (no transfer). The results show that the recognition performance achieved by ATTL with irrelevant prior objects is similar to the ones obtained with the ATL method (no-transfer) in the case of learning about objects via three physical properties (Fig. 12(a)) and via only one physical property (Fig. 12(b), Fig. 12(c), and Fig. 12(d)). This indicates that our proposed ATTL can stop transferring irrelevant prior knowledge.
Fig. 9. Confusion matrix for stiffness of 28 objects (prior objects (from 1 till 21) + new objects (22 till 28)). The blue index indicates the prior objects, and the red index new objects.

Fig. 10. Confusion matrix for surface texture of 28 objects (prior objects (from 1 till 21) + new objects (22 till 28)). The blue index indicates the prior objects, and the red index new objects.
6. Discussion

In this paper, we proposed an active tactile transfer learning algorithm to enable a robotic system with multi-modal artificial skin to actively leverage the prior tactile knowledge to learn new objects in the unknown workspace. Taking advantage of our previously proposed pre-touch exploration approach, the robotic system can strategically select the next exploratory location in the workspace to efficiently collect pre-touch information. The attained data were then used to ascertain the number and positions of the objects.

Using our proposed ATTL method, the robot discriminated among new objects with very high discrimination accuracy. It automatically leveraged the most relevant and informative prior knowledge to learn about new unknown objects with a low number of samples. The robot achieved 72% discrimination accuracy with only one training sample plus prior tactile knowledge (one-shot tactile learning). Besides, the robot automatically decided how much to re-use and transfer the prior tactile knowledge, or stop transferring the irrelevant knowledge which could degrade the learning performance (Fig. 12). Furthermore, the robot attained higher discrimination accuracy, when the number of its prior tactile knowledge increased (Fig. 7 and Fig. 8). This accounts for the fact that increasing the number of prior knowledge also enhances the probability of finding more relevant ones. The experimental results show that the ATTL outperformed uniform learning strategy in which the
Fig. 12. Evaluation of active tactile learning with negative prior knowledge constructed by deliberately selected five prior objects that were unrelated to the new objects. (a) Learning about the new objects based on three physical properties, prior objects: object \{2, 3, 6, 10, 13\}; (b) based on only stiffness, prior objects: object \{1, 2, 3, 10, 18\}; (c) based on only surface texture, prior objects: object \{6, 7, 9, 10, 21\}; (d) based on only thermal conductivity, prior objects: object \{4, 6, 8, 10, 13\}.

training data was collected uniformly and no past tactile experience was transferred. The ATTL also performed better than the ATL method, as by following the ATL, the robot was unable to exploit any past tactile experience, even though it strategically collected training samples.

On the contrary, by using the ATTL method the robotic system leveraged its prior tactile knowledge while learning about new objects. It strategically selected the next object to explore and next informative exploratory action to execute.

Besides, compared to our previous work (Kaboli et al.\cite{55,56}), our proposed ATTL method enables the robot to actively transfer multiple tactile knowledge (surface}
texture, stiffness, and thermal conductivity).

A limiting assumption of our work is that the positions of the experimental objects are fixed and also the objects are placed flat in X-Y plane in the workspace. Moreover, due to the low spatial resolution provided by the proximity sensors on the artificial skin, objects that are place very close to each other can hardly be clustered during workspace exploration. In order to relax these constraints, the spatial resolutions of the sensor array can be increased by fusing the proximity information and force signals while the robot touching the objects in the workspace.

In the future, we consider to cover the entire robotic arm with an artificial skin to facilitate the robot to explore the workspace in an arbitrary directions. The experimental results showed that increasing the number of prior knowledge improved the discrimination accuracy and learning performance. Despite this, having too many prior knowledge, e.g. 1000000 objects, will largely increase the computational complexity so that it takes too long for the robot to select the relevant prior information. Finding a solution to remove such a constrain in any transfer learning approach can be a new interesting challenge to tackle as a future research. Finally, in our future study, we will try to extend our proposed framework to transfer tactile knowledge from one robotic platform (e.g. a robotic arm) to another robotic platform (e.g. humanoid robot) that can be equipped with different sensing modalities.

7. Conclusion

In this study, we designed a novel active tactile transfer learning algorithm to enable the robotic systems to leverage their prior tactile experience while discriminating among new objects in an unknown environment with a low number of training samples or one sample (one-shot tactile learning). The effectiveness of our proposed technique was evaluated through online experiments and evaluations. Results show that our proposed method outperforms the uniform learning strategy as well as our previously proposed active tactile learning (ATL) method as baseline methods. Taking advantage of the attained prior tactile knowledge, the autonomous robot that used the ATTL method efficiently discriminated among new objects with 20% higher discrimination accuracy compared to the baseline strategies. Furthermore, the experimental results show that our proposed algorithm is robust against transferring irrelevant tactile knowledge (negative tactile knowledge).

Video

The video to this paper can be found in the following link: http://web.ics.ei.tum.de/~mohsen/videos/IJHR2017.mp4

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