International Journal of Humanoid Robotics

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

Mohsen Kaboli
The Institute for Cognitive Systems, Technical University of Munich
Arcisstrasse 21 80333, Munich, Germany
mohsen.kaboli@tum.de

Di Feng
The Institute for Cognitive Systems, Technical University of Munich
Arcisstrasse 21 80333, Munich, Germany
fengdi1015@gmail.com

Gordon Cheng
The Institute for Cognitive Systems, Technical University of Munich
Arcisstrasse 21 80333, Munich, Germany
gordon@tum.de

Received 30 April 2017
Revised 22 July 2017
Accepted 11 September 2017

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.[5] 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.[6–8]

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[9–12] or cutaneous receptors, by exhaustively touching a single object with a known orientation and location in the workspace.[13–15] 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.[16–21] The stiffness of objects can also be measured by pressing the robot fingertips against the objects.[22] Likewise, the thermal conductivity can be perceived by building light contact with the objects' surfaces.[23]

Previous researchers have used various robotic systems and tactile sensors to passively explore objects and discriminate among them.[24–30] 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.[31] 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.*[33] 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,[34] 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*[35] 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.*[32] 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.*[36] 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 inflective 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,[37] 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 re-use 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,[38–47] reinforcement learning,[48] data mining,[49–51] brain computer interface,[52] and deep learning,[53] 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 hands 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 filed 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[54] 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.

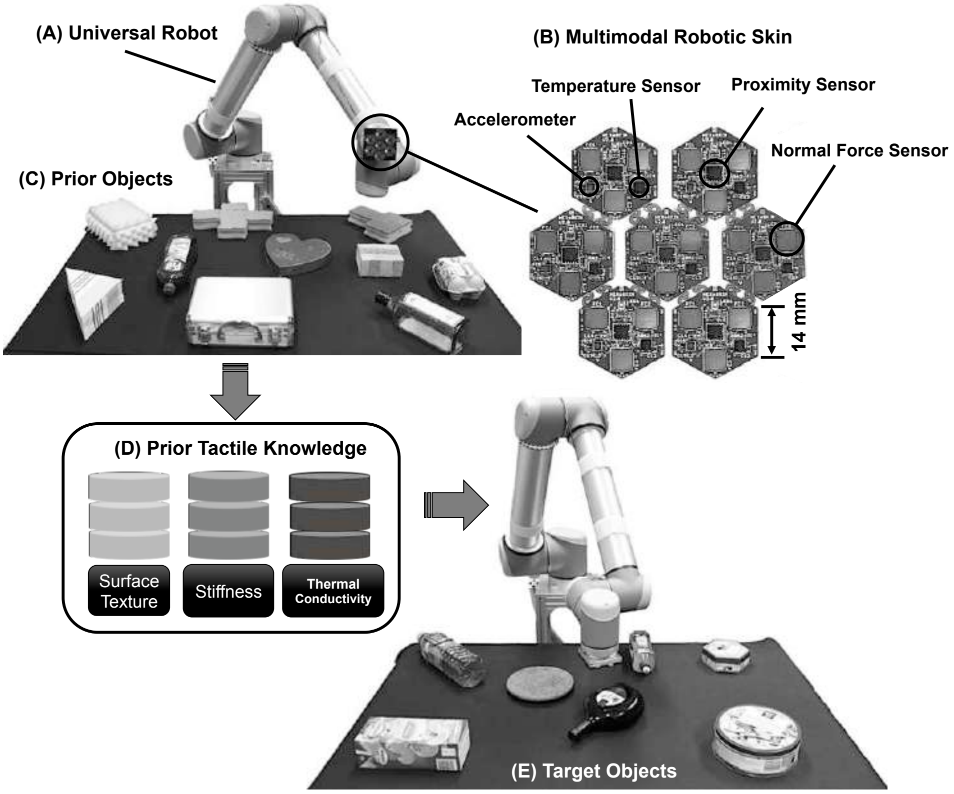


Fig. 1. The scenario of active tactile transfer learning for object discrimination in the unstructured environment. The robotic arm (A) equipped with multimodal artificial skin (B) can actively learn about prior objects via surface texture, stiffness, and thermal conductivity (C) in an unstructured environment 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.

Modality	**Acceleration**	**Force**	**Proximity**	**Temperature**
Sensor	BMA250	Customized	VCNL4010	LM71
Per Cell	1	3	1	1
Range	$\pm 2\,g$	$> 0 - 10\,N$	$1 - 200\,mm$	$-40 - 150\,^{\circ}\mathrm{C}$
Bandwidth	$0 - 1\,kHz$	$0 - 33\,kHz$	$0 - 250\,Hz$	$0 - 7\,Hz$

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)).

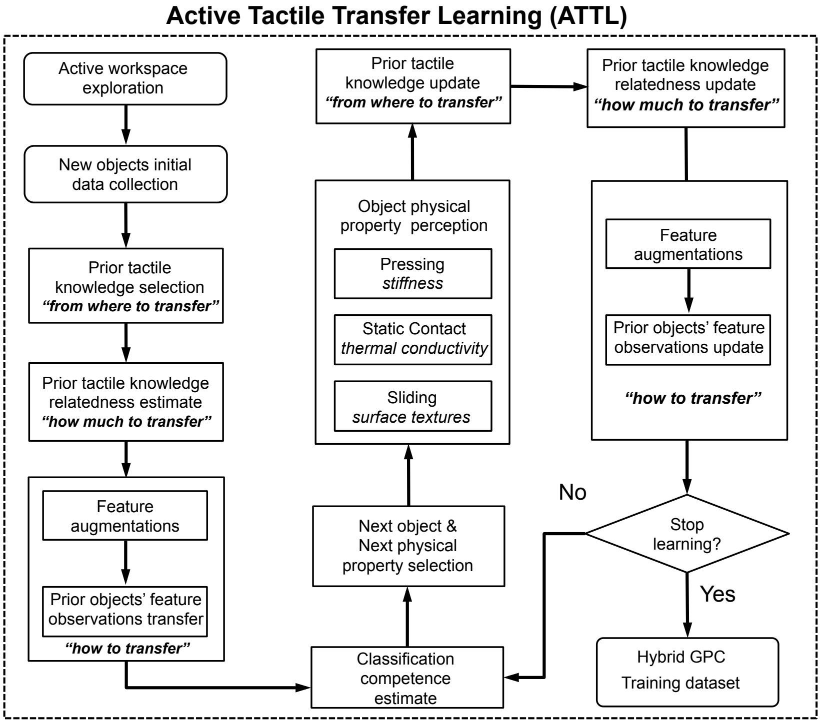


Fig. 2. The proposed method of the probabilistic tactile-based active tactile transfer learning for object discrimination in an unstructured environment.

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.

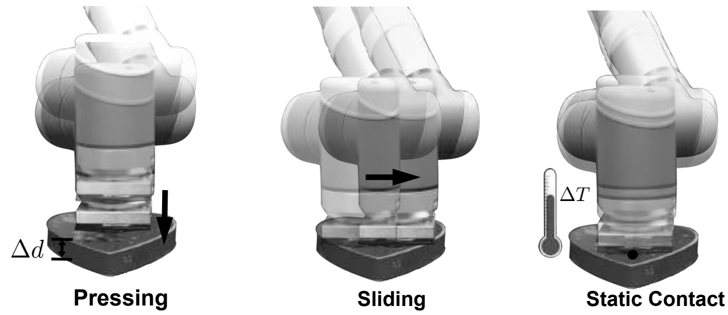


Fig. 3. Exploratory actions: pressing, sliding, and static contact

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_ϵ, i.e. $F_{av}>f_\epsilon$ ($N_c = 7$ 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 ($a^x_{n_c}$, $a^y_{n_c}$, $a^z_{n_c}$). 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 $\mathbf{A}_{total}$, $\mathbf{M}_{total}$, and $\mathbf{C}_{total}$, and $\mathbf{L}_{total}$ in Table 2. In all the equations, s_n and v_n are measured tactile signals. The final tactile descriptor $\mathbf{D}_{total}$ is the concatenation of all computed tactile features and can be defined as: $\mathbf{D}_{total} = [\mathbf{A}_{total};\ \mathbf{M}_{total};\ \mathbf{C}_{total};\ L_{total}]$.

Table 2. Tactile Feature Descriptors

$A(s_n) = \frac{1}{N}\sum_{n=1}^{N}(s_n - \bar{s})^2$
$M(s_n) = \left(A(\frac{ds_n}{dn})/A(s_n)\right)^{-1/2}$
$C(s_n) = M(\frac{ds_n}{dn})/M(s_n)$
$L(s_n, v_n) = \sum_{n=1}^{N}(s_n - \bar{s})(v_n - \bar{v})/\sigma(s_n)\sigma(v_n)$
$\mathbf{A}_{total} = \left[\sum_{n_c=1}^{N_c}\frac{A(a_{n_c}^x)}{N_c}, \sum_{n_c=1}^{N_c}\frac{A(a_{n_c}^y)}{N_c}, \sum_{n_c=1}^{N_c}\frac{A(a_{n_c}^z)}{N_c}\right]$
$\mathbf{M}_{total} = \left[\sum_{n_c=1}^{N_c}\frac{M(a_{n_c}^x)}{N_c}, \sum_{n_c=1}^{N_c}\frac{M(a_{n_c}^y)}{N_c}, \sum_{n_c=1}^{N_c}\frac{M(a_{n_c}^z)}{N_c}\right]$
$\mathbf{C}_{total} = \left[\sum_{n_c=1}^{N_c}\frac{C(a_{n_c}^x)}{N_c}, \sum_{n_c=1}^{N_c}\frac{C(a_{n_c}^y)}{N_c}, \sum_{n_c=1}^{N_c}\frac{C(a_{n_c}^z)}{N_c}\right]$
$\mathbf{L}_{total} = \left[\sum_{n_c=1}^{N_c}\frac{L(a_{n_c}^x, a_{n_c}^y)}{N_c}, \sum_{n_c=1}^{N_c}\frac{L(a_{n_c}^x, a_{n_c}^z)}{N_c}, \sum_{n_c=1}^{N_c}\frac{L(a_{n_c}^y, a_{n_c}^z)}{N_c}\right]$

3.2.3. *Thermal Conductivity Measurment*

A robot having the sense of touch can distinguish between objects by means of their thermal cues by applying a static contact with their surfaces. In our study, in order to measure the thermal conductivity of each object, UR10 establishes a contact by its skin with the surface of the objects for a certain period of time $t_{contact}$. during which the average temperature time series of the contacted area is recorded by the temperature sensors: $T_{total}{=}\{\frac{1}{N_c N_T}\sum_{n_c=1}^{N_c}\sum_{n_T=1}^{N_T} T_{n_c,n_T}^i\}_{i=1}^{t_{contact}}$, where N_T is the number of temperature sensors in each skin cell, and T_{n_c,n_T} represents the recordings of a temperature sensor. The final thermal feature (TC) is the combination of the average temperature time series and its gradient at each time step $\mathbf{TC} = [T_{total}, \nabla T_{total}]$. To avoid curse of dimensionality, we further reduce this combination to 10 dimensions via Principle Component Analysis (PCA) method and use it as the final thermal conductivity feature vector of each object.

4. Active Tactile Transfer Learning (ATTL)

We propose an active tactile transfer learning (ATTL) method to enable the robotic systems to leverage their captured prior tactile experience while learning about new objects via their physical properties with fewer training samples.

4.1. *Problem Definition*

Let us to consider a scenario in which the robotic system has already learned N_{prior} number of objects $O^{prior} = \{o_j^{prior}\}_{j=1}^{N_{prior}}$ 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 ($Z^{prior} = \{Z_{s_1}^{prior}, Z_{s_2}^{prior}, Z_{s_3}^{prior}\}$) and their constructed reliable observation models denoted by $Z^{prior} \xrightarrow{\mathbf{f}^{prior}} O^{prior}$ (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_{new} number of new objects as $O^{new} = \{o_i^{new}\}_{i=1}^{N_{new}}$. 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 $Z^{new} \xrightarrow{\mathbf{f}^{new}} O^{new}$ with the feature observations $Z^{new} = \{Z_{s_1}^{new}, Z_{s_2}^{new}, Z_{s_3}^{new}\}$ for each of the physical properties perceived during the exploration of the *new objects*, while tre-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 $X \xrightarrow{\mathbf{f}} Y$, 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 $X \xrightarrow{\mathbf{g}} \mathbb{R}$, which is sampled by the GP prior:[60] $\mathbf{g}|X \sim \mathcal{GP}(\mathbf{0}, K(X, X))$ 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 ($\mathbf{f}_n(\cdot)$) is learned, with its hyper-parameters being optimized through maximizing the log likelihood. 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 predicted probability:

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

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^{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 $\mathbf{f}^{prior}(\cdot)$ and feature observations Z^{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^{prior}, and i as the new object o_i^{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 $p(o_j^{prior}|\mathbf{v}_{s,i}^{new})$ to be as a prediction from the prior object's (o_j^{prior}) observation model with regard to the physical property s.
Here, $\mathbf{v}_{s,i}^{new}$ is a feature observation from the new object o_i^{new}. We calculate the average prediction to all $N_{s,i}^{new}$ number of samples that belong to the new object o_i^{new} by $\bar{p}(o_j^{prior}|Z_{s,i}^{new}) = \frac{1}{N_{s,i}^{new}} \sum p(o_i^{new}|\mathbf{v}_{s,i}^{new})$. This value estimates the relatedness of the physical property s between the prior object o_j^{prior} and the new object o_i^{new}. The higher the value is, the more similar two objects are. Thus, the prior object with the largest average prediction value (denoted as $o_{s,i}^{prior^*}$) can be selected to transfer its feature observations of the physical property s to the new objects :

$$o_{s,i}^{prior^*} = \underset{o^{prior} \in O^{prior}}{\arg\max}\ \bar{p}(o_j^{prior}|Z_{s,i}^{new}). \tag{2}$$

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^{prior}) feature observations $Z_{s,j}^{prior}$ of the physical property "s" to the new object o_i^{new}, we define $\mathbf{g}_{s,j}^{prior}$ and $\mathbf{g}_{s,i}^{new}$ to be the latent functions of the GPC models constructed by the feature observations from prior objects $Z_{s,j}^{prior}$ and new object $Z_{s,i}^{new}$ 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:

$$\mathbf{g}_{s,i}^{new} \leftarrow [\mathbf{g}_{s,j}^{prior}; \mathbf{g}_{s,i}^{new}], \tag{3}$$

the kernel function can be defined as:

$$K = \begin{pmatrix} K^z(Z_j^{prior}, Z_j^{prior}) & \gamma K^z(Z_j^{prior}, Z_i^{new}) \\ \gamma K^z(Z_i^{new}, Z_j^{prior}) & K^z(Z_i^{new}, Z_i^{new}) \end{pmatrix}. \tag{4}$$

where K^z is the base kernel function that measures the similarity of training samples. In our case, we use radial basis function (RBF),[60] whose hyper-parameters are found by maximizing the log-likelihood of this hybrid GPC model.

In Eq. 4, $K^z(Z_j^{prior}, Z_j^{prior})$ and $K^z(Z_i^{new}, Z_i^{new})$ measure the similarity for feature observations of the prior object and the new object respectively. And $\gamma K^z(Z_j^{prior}, Z_i^{new})$ and $\gamma K^z(Z_i^{new}, Z_j^{prior})$ measure the similarity between the feature observations of the prior object and the new object respectively. The parameter γ ranges between 0 and 1. As analyzed by Chai et al.,[61] γ 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 γ by the average prediction probability of the training samples:

$$\gamma = \begin{cases} \bar{p}(o_j^{prior} | Z_{s,i}^{new}) & \text{if } \bar{p}(o_j^{prior} | Z_{s,i}^{new}) > \epsilon_\gamma, \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

with ϵ_γ 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 γ 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 $\mathbf{v}$ can be defined as:

$$\mathbf{v}' = \Big[\underbrace{\mathbf{v};}_{\text{Original feature observation}} \underbrace{p(o_1^{prior}|\mathbf{v}); p(o_2^{prior}|\mathbf{v}); ...; p(o_{N_{prior}}^{prior}|\mathbf{v})}_{\text{Prior tactile knowledge}} \Big]. \tag{6}$$

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).[37]

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 : $O^{new} = \{o_i^{new}\}_{i=1}^{N_{new}}$, $L^{new} = \{\mathbf{l}_{o_i^{new}}\}_{i=1}^{N_{new}}$ ▷ 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}, $Z^{prior} \xrightarrow{\mathbf{f}^{prior}} O^{prior}$ ▷ Prior knowledge

Output: $Z^{new'} \xrightarrow{\mathbf{f}^{new}} O^{new}$, $Z^{new'}$ ▷ New objects' GPCs and feature observations.

Initialization: Z^{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**
  for $i = 1 : N_{new}$ **do**
    $o_{s,i}^{prior^*} \leftarrow priorKnowledgeSelection(\bar{p}(o_j^{prior}|Z_{s,i}^{new})$ ▷ Sec. 4.2.1
    $\gamma_{s,i} \leftarrow correlationEstimate(o_{s,i}^{prior^*}, \bar{p}(o_j^{prior}|Z_{s,i}^{new}))$ ▷ Eq. 5
    $Z_{s,i}^{new'} \leftarrow featureAugmentation(Z_{s,i}^{new})$ ▷ Eq. 6
    $\mathbf{f}_{s,i}^{new}(\cdot) \leftarrow updateGPC(Z_{s,i}^{new'}, \gamma_{s,i})$ ▷ Sec. 4.2.2
  end
end

$Z^{new'} = \{Z_{s_1,i}^{new'}, Z_{s_2,i}^{new'}, Z_{s_3,i}^{new'}\}_{i=1}^{N_{new}}$
$\mathbf{f}^{new}(\cdot) = \{\mathbf{f}_{s_1,i}^{new}(\cdot), \mathbf{f}_{s_2,i}^{new}(\cdot), \mathbf{f}_{s_3,i}^{new}(\cdot)\}_{i=1}^{N_{new}}$

while *not stop condition*() **do**
  New Feature Observation Collection
  $\Lambda(s, o_i^{new}) \leftarrow competenceEstimation(\mathbf{f}^{new}(\cdot))$ ▷ Eq. 8
  $\lambda(s^*, o^{new^*}) \leftarrow objectPropertySelection(\Lambda(s, o_i^{new}))$ ▷ Eq. 9
  $moveTo(\mathbf{l}_{o^{new*}})$ ▷ Robot moves to the object
  $\mathbf{v}^{new} \leftarrow actionExecution(s^*)$ ▷ Get new training sample
  $Z^{new} \leftarrow Z^{new} \bigcup \mathbf{v}^{new}$ ▷ Update training database
  Update prior tactile knowledge
  for $i = 1 : N_{new}$ **do**
    $o_{s^*,i}^{prior^*} \leftarrow priorKnowledgeSelection(\bar{p}(o_j^{prior}|Z_{s^*,i}^{new});$
    $\gamma_{s^*,i} \leftarrow correlationEstimate(c_{s^*,i}^{*prior}, \bar{p}(o_j^{prior}|Z_{s^*,i}^{new}))$
    $Z_{s^*,i}^{new'} \leftarrow featureAugmentation(Z_{s^*,i}^{new})$
    $\mathbf{f}_{s^*,i}^{new}(\cdot) \leftarrow updateGPC(Z_{s^*,i}^{new'}, \gamma_{s^*,i})$
  end
end

First, the robot measures the Shannon entropy of each new objects' feature observation that has been collected $\mathbf{v}^{new} \in Z^{new}$:

$$\mathcal{H}(\mathbf{v}^{new}) = -\sum_{o_i^{new} \in O^{new}} p(o_i^{new}|\mathbf{v}^{new}) \log(p(o_i^{new}|\mathbf{v}^{new})). \tag{7}$$

Then the training data set Z^{new} is divided into categories according to the physical property s and object class o_i^{new}. The GPC's classification competence $\Lambda(s, o_i^{new})$ is estimated as the mean value of the Shannon entropy:

$$\Lambda(s, o_i^{new}) = \frac{1}{N_{s,i}^{new}} \sum_{\mathbf{v}^{new} \in Z_{s,i}^{new}} \mathcal{H}(\mathbf{v}^{new}). \tag{8}$$

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

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

$$\lambda(s^*, o^{new^*}) = \begin{cases} \underset{s \in \{s_1, s_2, s_3\}, o_i^{new} \in O^{new}}{\arg\max} \Lambda(s, o_i^{new}), & \text{if } p_\lambda > \epsilon_\lambda, \\ \\ s^* = \mathcal{U}\{s_1, s_2, s_3\},\ o^{new^*} = \mathcal{U}\{o_1^{new}, ..., o_{N_{new}}^{new}\}, & \text{otherwise.} \end{cases} \tag{9}$$

where ϵ_λ is the parameter to control the exploration-exploitation trade-off.[37] p_λ is a probability which is uniformly generated with $\mathcal{U}(0, 1)$ at each learning iteration.

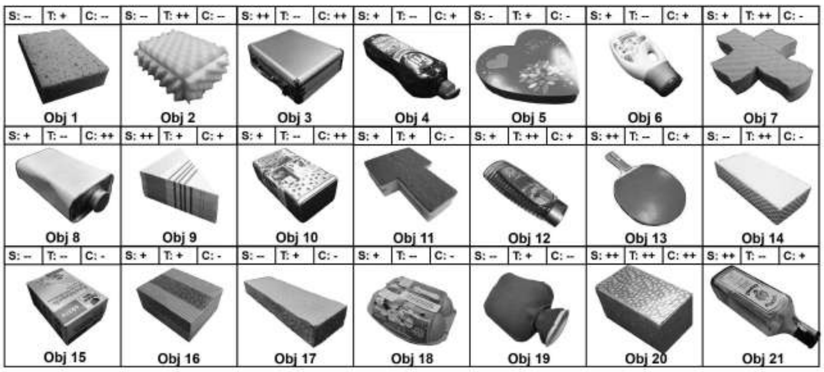
5. Experimental Results

5.1. *Experimental Objects*

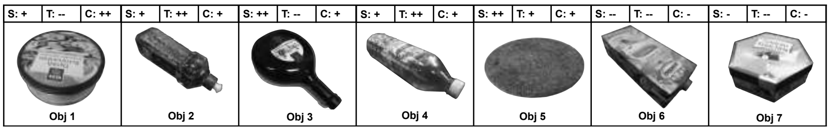
In order to assess our proposed ATTL method, we deliberately selected two sets of objects, one set with 21 objects as prior objects (Fig. 4(a)) and another set with 7 objects as new objects (Fig. 4(b)). All experimental objects were made by different materials (such as glass, cardboard, and plastic) 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[37] to explore the unknown workspace and estimate their



(a)



(b)

Fig. 4. **(a)**: Prior objects. **(b)**: New objects. The physical properties are evaluated subjectively by human subjects (S: stiffness, T: roughness of surface textures, C: thermal conductivity. "++": very high; "+": high; "-": low; "- -": very low.)

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.

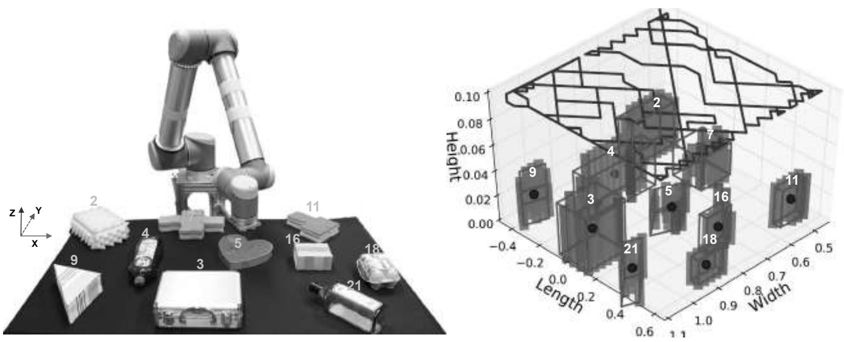
5.3. *Workspace Exploration*

Fig. 5(a) illustrates the unknown workspace which is a cuboid of $110cm \times 64cm \times 10cm$ ($L \times W \times H$). 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



(a) The unknown workspace (b) Active pre-touch

Fig. 5. **(a)**: The unknown workspace which the robot explored. **(b)**: Trajectories of the robot's end-effector during the exploration of the workspace and the localization results using active pre-touch strategy.[37]

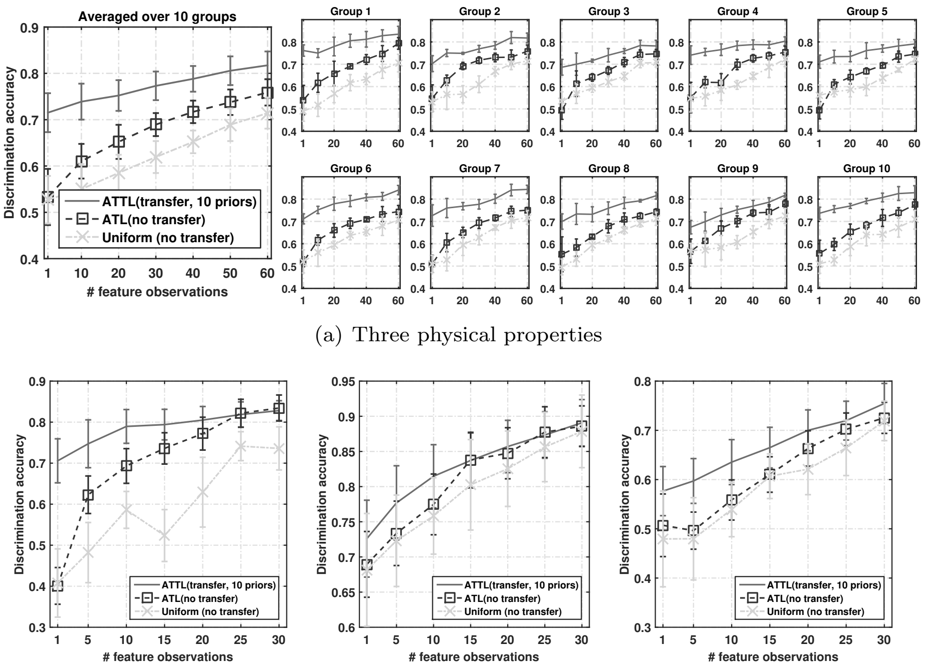
automatically performed each exploratory action 20 times on each of the prior objects. It begun to apply each of the exploratory action with a light contact with each object with approximately $0.05N$. For the pressing movement, the robot first pressed the end-effector $2mm$ on the objects' surface and then recorded the outputs of the normal force sensors for $3s$. To perceive the surface texture of the objects, the robotic slid its artificial skin on the objects with velocity of $1cm/s$ for $3s$ (in order to collect fair tactile information with all experimental objects). When measuring the thermal conductivity, the robot pressed its sensitive part $2mm$ on the objects' surfaces and held it for $15s$. Then it kept its end-effector up for $30s$ 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[37] 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[37] to strategically select the next object to perceive and the next physical property to explore, however, it was



(a) Three physical properties

(b) Stiffness (c) Surface texture (d) Thermal conductivity

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.

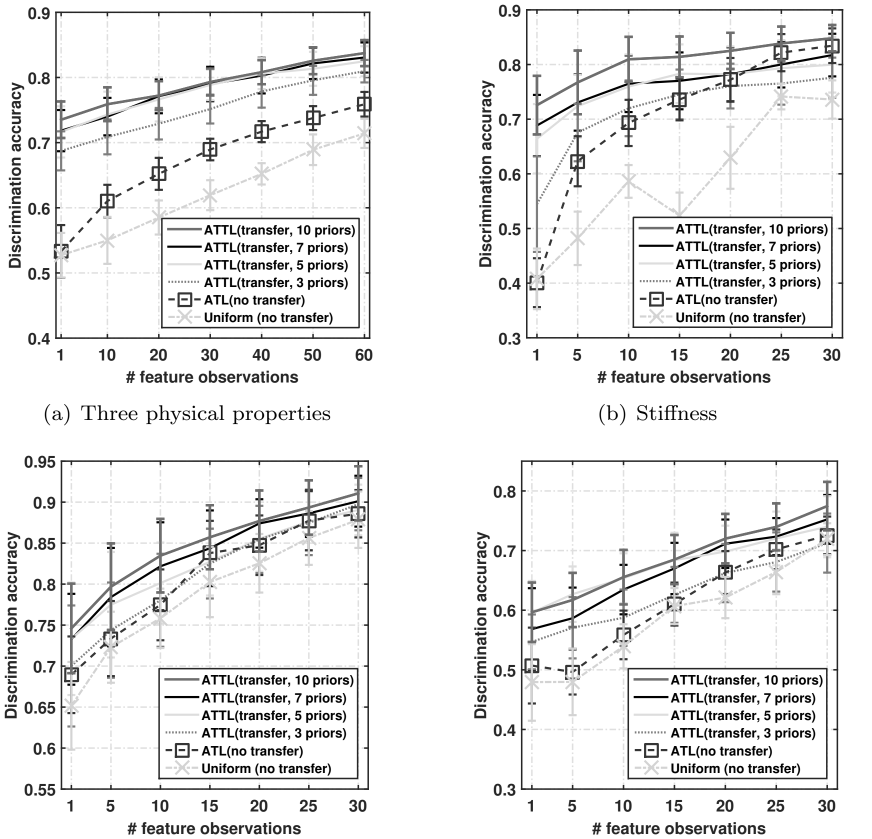
We also evaluated ATTL when the robot used only one of the physical properties (stiffness, surface texture and thermal conductivity) to learn about new objects. In this instance, the total number of feature observations was set to 30. Fig. 6(b), Fig. 6(c) and Fig. 6(d) show that in all three cases, the 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



(a) Three physical properties (b) Stiffness

(c) Surface texture (d) Thermal conductivity

Fig. 7. Evaluation of the ATTL performance using different number of prior objects. **(a)** Learning about the new objects based on three physical properties; **(b)** based on only stiffness; **(c)** based on only surface texture; **(d)** based on only thermal conductivity.

5%. Such improvement increases to over 10% when the robot leveraged 10 prior objects to learn about new objects.

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

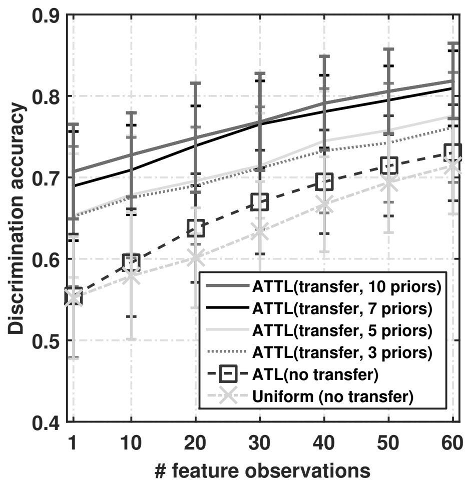


Fig. 8. Learnining about new objects with different number of prior objects. The new objects and the prior objects were randomly selected, following the uniform distribution.

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.

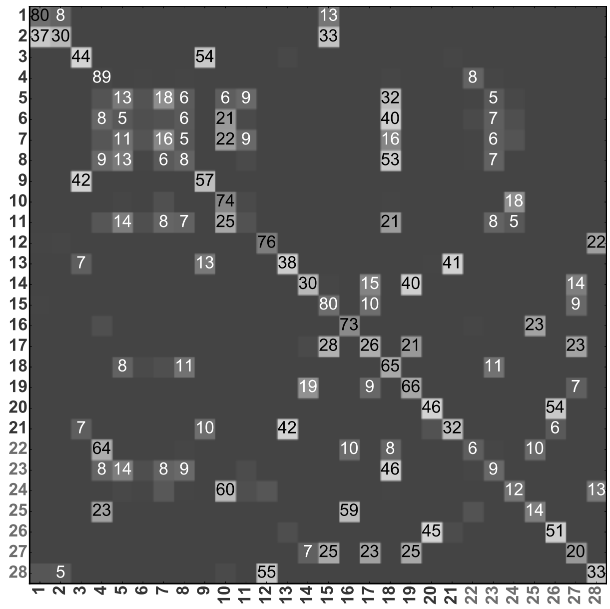


Fig. 9. Confusion matrix for stiffness of 28 objects (prior objects (from 1 till 21) + new objects (22 till 28)). The blue index indicates the prior objects, and the red index new objects.

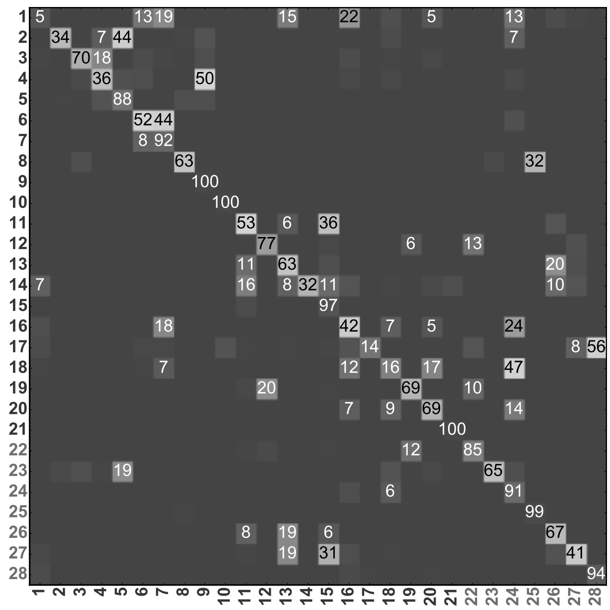


Fig. 10. Confusion matrix for surface texture of 28 objects (prior objects (from 1 till 21) + new objects (22 till 28)). The blue index indicates the prior objects, and the red index new objects.

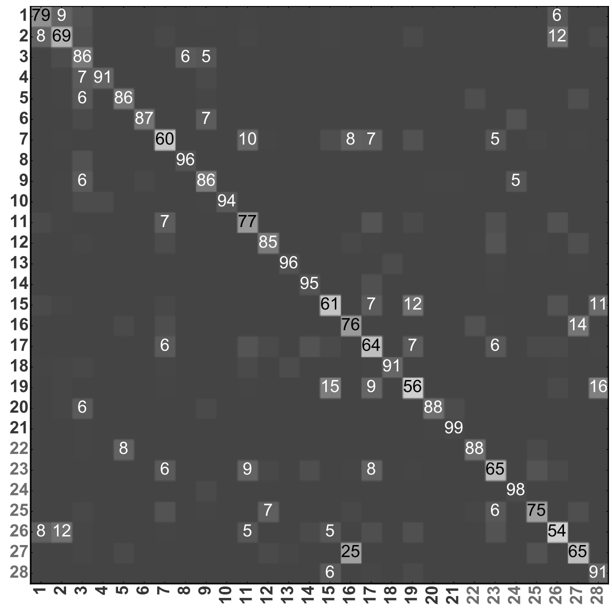
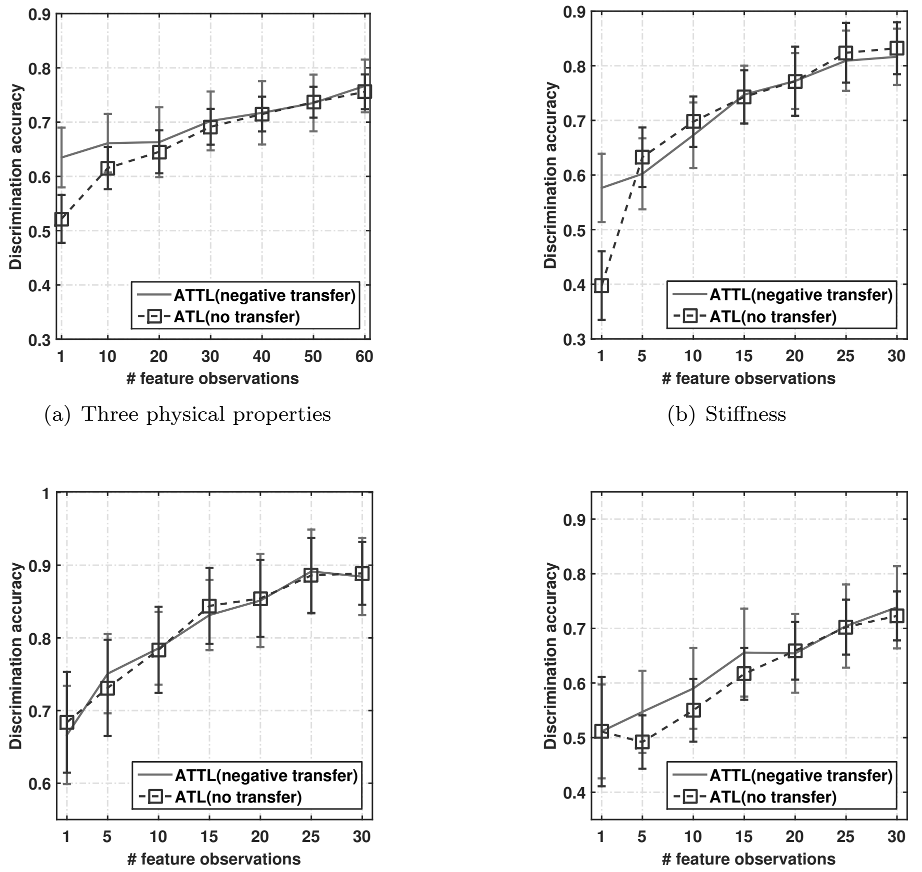


Fig. 11. Confusion matrix for thermal conductivity of 28 objects (prior objects (from 1 till 21) + new objects (22 till 28)). The blue index indicates the prior objects, and the red index new objects.

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



(a) Three physical properties

(b) Stiffness

(c) Surface texture

(d) Thermal conductivity

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 transfered. 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.*[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 constrains, 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

Acknowledgement

We would like to thank Kunpeng Yao and Zhiliang Wu for their help during experiments.

References

1. N. Yogeswaran, W. Dang, W.T. Navaraj, D. Shakthivel, S. Khan, E.O. Polat, S. Gupta, H. Heidari, M. Kaboli, L. Lorenzelli, G. Cheng, and R. Dahiya. New materials and advances in making electronic skin for interactive robots. *Advanced Robotics* (2015), 29(21),1359–1373
2. Mohsen Kaboli, Kunpeng Yao, and Gordon Cheng. Tactile-based manipulation of deformable objects with dynamic center of mass, *IEEE International Conference on Humanoid Robots (Humanoids)* (2016), p. 752–757.
3. Kunpeng Yao, Mohesn Kaboli, and Gordon Cheng. Tactile-based object center of mass exploration and discrimination, *IEEE International Conference on Humanoids Robot (Humanoids)* (2017).
4. Mohsen Kaboli, Alex Long, and Gordon Cheng. Humanoids learn touch modalities identification via multi-modal robotic skin and robust tactile descriptors. *Advanced Robotics*, 29(21):1411–1425, 2015.
5. G. Westling and R. S. Johannson Factors influencing the force control during precision grip, *Experimental Brain Research* (1984), 53 p. 277–284.
6. G. Robles-De-La-Torre, The importance of the sense of touch in virtual and real environments, *IEEE MultiMedia* (2006), p. 24–30.
7. S. Somlor, R. S. Hartanto, A. Schmitz, S. Sugano, A Novel Tri-axial Capacitive-Type Skin Sensor, *Advanced Robotics* (2015), 29(21), p. 1375-1391.
8. T. P. Tomo, W. K. Wong, A. Schmitz, H. Kristanto, A. Sarazin, L. Jamone, S. Somlor, S. Sugano, A modular, distributed, soft, 3-axis sensor system for robot hands, *IEEE International Conference on Humanoid Robots* (2016). p. 454-460.
9. H. Liu, J. Greco, X. Song, J. Bimbo, and K. Althoefer, Tactile Image Based Contact Shape Recognition Using Neural Network, *IEEE I nternational Conference on Intelligent Robots and Systems* (2013), p. 2539–2544.
10. H. Liu, Song, T. Nanayakkara, L. D. Seneviratne, and K. Althoefer, A Computationally Fast Algorithm for Local Contact Shape and Pose Classification using a Tactile Array Sensor, *IEEE International Conference on Robotics and Automation* (2012), p.1410–1415.
11. Y. Jia, and J. Tian, Surface Patch Reconstruction From 'One-Dimensional' Tactile Data, *IEEE Transactions on Automation Science and Engineering* (2010), p. 400–407.
12. M. V. Liarokapis, B. Calli, A. J. Spiers, and A. M. Dollar, Unplanned, model-free, single grasp object classification with underactuated hands and force sensors, *IEEE International Conference on Intelligent Robots and Systems* (2015), p. 5073–5080.
13. T. Matsubara and K. Shibata, Active tactile exploration with uncertainty and travel cost for fast shape estimation of unknown objects, *Robotics and Autonomous Systems* (2017), p. 314–326.
14. H. Liu, K. C. Nguyen, V. Perdereau, J. Bimbo, J. Back, M. Godden, L. D. Seneviratne, and K. Althoefer, Finger contact sensing and the application in dexterous hand manipulation, *Autonomous Robots* (2015), p. 25–41.
15. Nawid Jamali, Carlo Ciliberto, Lorenzo Rosasco, and Lorenzo Natale, Active Perception: Building Objects Models using Tactile Exploration, *IEEE International Conference on Humanoid Robots* (2016), p. 179-185.
16. P. Dallaire, P. Giguere, D. Edmond, and B. Chaib-draa, Autonomous tactile perception: A combined improved sensing and Bayesian nonparametric approach, *Robotics and Autonomous Systems* (2014), p. 422–435.
17. P. Giguere, and G. Dudek, A Simple Tactile Probe for Surface Identification by Mobile Robots, *IEEE Transactions on Robotics* (2011), p. 534–544 .
18. K. Watanabe, M. Sohgawa, T. Kanashima, M. Okuyama, and H. Norna, Identification

of various kinds of papers using multi-axial tactile sensor with micro-cantilevers, *World Haptics Conference* (2013), p. 139-144.

19. D. S. Chathuranga, Z. Wang, V. A. Ho, A. Mitani, and S. Hirai, A biomimetic soft fingertip applicable to haptic feedback systems for texture identification, *IEEE International Symposium on Haptic Audio Visual Environments and Games* (2013), p. 29–33.
20. N. Jamali, and C. Sammut, Majority Voting: Material Classification by Tactile Sensing Using Surface Texture, *IEEE Transactions on Robotics* (2011), p. 508–521.
21. V. Chu, I. McMahon, L. Riano, C. G. McDonald, and Q. He, and others, Using robotic exploratory procedures to learn the meaning of haptic adjectives, *IEEE International Conference on Robotics and Automation* (2013), p. 3048–3055.
22. S. J. Lederman, The perception of surface roughness by active and passive touch, *Bulletin of the Psychonomic Society* (1981), p. 253–255.
23. T. Bhattacharjee, J. Wade, and C. C. Kemp, Active tactile exploration with uncertainty and travel cost for fast shape estimation of unknown objects, *Proceedings of Robotics: Science and Systems* (2015), p. 297–304.
24. Jivko Sinapov, Vladimir Sukhoy, Ritika Sahai, and Alexander Stoytchev, Vibrotactile recognition and categorization of surfaces by a humanoid robot, *IEEE Transactions on Robotics* (2011), p. 488–497.
25. H. Hu, Y. Han, A. Song, S. Chen, C. Wang, and Z. Wang, A Finger-Shaped Tactile Sensor for Fabric Surfaces Evaluation by 2-Dimensional Active Sliding Touch, *Sensors* (2014), p. 4899–4913.
26. W. W. Mayol-Cuevas, J. Juarez-Guerrero, and S. Munoz-Gutierrez, A first approach to tactile texture recognition, *IEEE International Conference on Systems, Man, and Cybernetics* (1998), p. 4246–4250.
27. N. H. H. Mohamad Hanif, P. H. Chappell, A. Cranny, and N. M. White, Surface texture detection with artificial fingers, *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (2015), p. 8018–8021.
28. A. Song, Y. Han, H. Hu, and J. Li, A novel texture sensor for fabric texture measurement and classification, *IEEE Transactions on Instrumentation and Measurement* (2014), p. 1739–1747.
29. K. E. Friedl, A. R. Voelker, A. Peer, and C. Eliasmith, Human-Inspired Neurorobotic System for Classifying Surface Textures by Touch, *IEEE Robotics and Automation Letters* (2016), p. 516–523.
30. N. F. Lepora, M. Evans, C. W. Fox, M. E. Diamond, K. Gurney, and T. J. Prescott, Naive Bayes texture classification applied to whisker data from a moving robot, *The International Joint Conference on Neural Networks* (2010), p.1–8.
31. H. P. Saal, J. A. Ting, and S. Vijayakumar, Active Sequential Learning with Tactile Feedback, *AISTATS* (2010), p. 677–684.
32. Danfei Xu, Gerald E. Loeb, and Jeremy A. Fishel, Tactile identification of objects using Bayesian exploration, *IEEE International Conference on Robotics and Automation* (2013), p. 3056–3061.
33. Nathan F. Lepora, Uriel Martinez-Hernandez, and Tony J. Prescott, Active touch for robust perception under position uncertainty, *IEEE International Conference on Robotics and Automation* (2013), p. 3020–3025.
34. Alexander Schneider, Jürgen Sturm, Cyrill Stachniss, Marco Reisert, Hans Burkhardt, and Wolfram Burgard, Object identification with tactile sensors using bag-of-features, *IEEE International Conference on Intelligent Robots and Systems* (2009), p. 243–248.
35. R. Martins, J. F. Ferreira, and J. Dias, Touch attention Bayesian models for robotic active haptic exploration of heterogeneous surfaces, *International Conference on Intel-*

ligent Robots and Systems (2014), p. 1208–1215.
36. Daisuke Tanaka, Takamitsu Matsubara, Kentaro Ichien, and Kenji Sugimoto, Object manifold learning with action features for active tactile object recognition, *IEEE International Conference on Intelligent Robots and Systems* (2014), p. 608–614.
37. M. Kaboli, D. Feng, K. Yao, P. Lanillos, and G. Cheng, A Tactile-based Framework for Active Object Learning and Discrimination using Multi-modal Robotic Skin, *IEEE Robotics and Automation Letters* (2017), 2(4), p. 2143–2150
38. S. J. Pan and Q. Yang, A Survey on Transfer Learning, *IEEE Transactions on Knowledge and Data Engineering* (2010), p. 1345–1359.
39. C. Goring, E. Rodner, A. Freytag, and J. Denzler, Nonparametric Part Transfer for Fine-grained Recognition, *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2014), p. 2489-2496.
40. G. Skolidis and G. Sanguinetti, Semisupervised Multitask Learning With Gaussian Processes, *IEEE Transactions on Neural Networks and Learning Systems* (2013), p. 12101–2112.
41. L. Fei-Fei, R. Fergus, and P. Perona, One-Shot Learning of Object Categories, *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2006), p. 594–611.
42. S. I. Lee, V. Chatalbashev, D. Vickrey, and D. Koller, Learning a meta-level prior for feature relevance from multiple related tasks, *In Proceedings of the 2007 international conference on Machine learning* (2007), p. 489–496.
43. A. Vedaldi, G. Guidi, and S. Soatto, Joint Alignment up to (Lossy) Transformations, *In Proceedings of the 2008 IEEE Conference on Computer Vision and Pattern Recognition* (2008), p. 1-8.
44. Mohesn Kaboli. Leveraging over prior knowledge for online learning of visual categories across robots. *Thesis, KTH, The Royal Institute of Technology, Stockholm Sweden*, (2012).
45. V. Jain and E. Learned-Miller, Online Domain Adaptation of a Pre-Trained Cascade of Classifiers, *In Proceedings of the 2008 IEEE Conference on Computer Vision and Pattern Recognition* (2011), p. 577-584.
46. R. Salakhutdinov, A. Torralba, and J. Tenenbaum, Learning to Share Visual Appearance for Multiclass Object Detection, *In Proceedings of the 2008 IEEE Conference on Computer Vision and Pattern Recognition* (2011), p. 1481-1488.
47. T. Tommasi, F. Orabona, M. Kaboli, and B. Caputo. Leveraging over prior knowledge for online learning of visual categories. *British Machine Vision Conference (BMVC)*, (2012).
48. R. Urtasun, A. Quattoni, N. D. Lawrence, and T. Darrell, Transfer learning for reinforcement learning domains: A survey, *The Journal of Machine Learning Research* (2011), p.1633–1685.
49. C. Do and A. Ng, Transfer learning for text classification, *In Advances in Neural Information Processing Systems* (2006), p. 299–306.
50. Q. Wu, X. Zhou, Y. Yan, H. Wu, and H. Min, Online transfer learning by leveraging multiple source domains. Knowledge and Information Systems, *In Knowledge and Information Systems* (2017), p. 1-21.
51. J. T. Zhou, J .P. Sinno, W. T. Ivor, and H. Shen-Shyang, Transfer Learning for Cross-Language Text Categorization through Active Correspondences Construction, *In AAAI* (2016), p. 2400–2406.
52. V. Jayaram, M. Alamgir, Y. Altun, B. Scholkopf, and M. Grosse-Wentrup, Transfer learning in brain-computer interfaces, *Pattern Recognition* (2016), p. 20–31.
53. J. W. Tao, D. Song, S. Wen, Wenjun Hu, Transfer Learning for Deep Learning on Graph-Structured Data, *Pattern Recognition* (2017), p. 47–65 .

54. P. Mittendorfer, and G. Cheng, Humanoid Multimodal Tactile-Sensing Modules, *IEEE Transactions on Robotics* (2011), p. 401–410.
55. M. Kaboli, R. Walker, and G. Cheng, Re-using prior tactile experience by robotic hands to discriminate in-hand objects via texture properties, *IEEE International Conference on Robotics and Automation (ICRA)* (2016), p. 2242–2247.
56. M. Kaboli and G. Cheng. Novel tactile descriptors and a tactile transfer learning technique for active in-hand object recognition via texture properties. *IEEE International Conference on Humanoid Robots (Humanoids)-workshop on tactile sensing for manipulation: new progress and challenges* (2016).
57. M. Kaboli, P. Mittendorfer, V. Hügel, and G. Cheng, Humanoids learn object properties from robust tactile feature descriptors via multi-modal artificial skin, *IEEE International Conference on Humanoid Robots* (2014), p.187–192.
58. M. Kaboli, T. De La Rosa, R. Walker, and G. Cheng, In-hand object recognition via texture properties with robotic hands, artificial skin, and novel tactile descriptors, *IEEE International Conference on Humanoid Robots* (2015), p. 155–1160.
59. Mohsen Kaboli and Gordon Cheng, Robust tactile descriptors for discriminating objects from textural properties via artificial robotic skin. *IEEE Transactions on Robotics Journal, under review* (2017).
60. C. E. Rasmussen and C. K. I. Williams, Gaussian Processes for Machine Learning, *the MIT Press*, (2006).
61. Kian M. Chai, Generalization errors and learning curves for regression with multi-task Gaussian processes, *Advances in neural information processing systems* (2009), p. 279–287.

Mohsen Kaboli received his bachelor degree in electrical and electronic engineering and master degree in signal processing and machine learning from the Royal Institute of Technology (KTH) in Sweden, in 2011. In March 2012, he received a scholarship from the Swiss National Foundation for 18 months in order to continue his research as a research assistant at the Idiap lab, Ecole Polytechnique Federale de Lausanne (EPFL). April 2013, he was awarded a three-year Marie Curie scholarship. Since that time he has been at the Institute for Cognitive Systems directed by Prof. Gordon Cheng in Technical University of Munich (TUM). In November 2013, he visited the Shadow Robot Company for two months. Mohsen has been a visiting researcher at the Human Robotics lab, department of Bioengineering at Imperial College London supervised by Prof. Ettien Burdet from February till April 2014. From September 2015 till January 2016, he spent 5 months as a visiting research scholar at the Intelligent Systems and Informatics lab at the University of Tokyo, Japan.

Di Feng was born in Kunming, China, in 1991. He is pursuing the master degree in electrical and computer engineering at the Technical University of Munich. He received the bachelor degree in mechatronics with honor from Tongji University, in 2014. During his bachelor study, he received DAAD scholarship and visited Niederrhein University of Applied Science as exchange student from Sep. 2013 till Aug 2014. His current research is centered on robotic active learning and exploration through tactile sensing. He is interested in perception, lifelong learning machines and cognitive systems.

Gordon Cheng is the Professor and founding director of the Institute for Cognitive Systems, Technical University of Munich, Germany. Prof. Cheng is speaker of the established Elite Master of Science program in Neuroengineering (MSNE) of the Elite Network of Bavaria. He is also involved in a large number of major European Union Projects (e.g. RoboCub, Factory-in-a-Day, CONTEST-ITN, RoboCom-Flagship). He held fellowships from the Center of Excellence and the Science and Technology Agency of Japan. Both of these fellowships were taken at the Humanoid Interaction Laboratory, Intelligent Systems Division at the Electrotechnical Laboratory, Japan. Formerly, he was the Head of the Department of Humanoid Robotics and Computational Neuroscience, ATR Computational Neuroscience Laboratories, Kyoto, Japan. He was the Group Leader for the JST International Cooperative Research Project (ICORP), Computational Brain. He has also been designated as a Project Leader/Research Expert for National Institute of Information and Communications Technology (NICT) of Japan. He received the Ph.D. degree in systems engineering from the Department of Systems Engineering, The Australian National University, in 2001, and the bachelor degrees in computer science from the University of Wollongong, Wollongong, Australia, in 1991 and 1993, respectively. He was the Managing Director of the company G.T.I. Computing in Australia. His current research interests include humanoid robotics, cognitive systems, brain machine interfaces, biomimetic of human vision, human-robot interaction, active vision, and mobile robot navigation. ns in humanoid robotic systems and neurorobotics. He is the co-inventor of approximately 15 patents and has co-authored approximately 350 technical publications, proceedings, editorials, and book chapters.