Dexterous Hands Learn To Re-Use The Past Experience To Discriminate In-Hand Objects From The Surface Textures

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Abstract— **This paper focuses on the problem of in-hand object recognition with anthropomorphic robotic hands via artificial robotic skin. Using our proposed batch tactile transfer learning technique, the robotic hands can re-use their prior tactile knowledge to discriminate in-hand objects while using few number of training samples. The experimental results show that the Shadow Hand could manage to classify in-hand objects with 100% recognition accuracy rate while using few training samples plus its past tactile experience.**

I. Introduction

Touch information is crucial for autonomous robots for detecting and learning the physical properties of every day objects. The performance of tactile systems depend not only on the technological aspect of the sensory device but also on the design of the learning methods that decipher and interpret information contained in tactile data. [1]–[5]. The tactile learning algorithms have been used so far are the traditional learning methods which are not designed to be updated often during learning tasks.

Contribution: In real-world applications collecting many data is costly and not always possible. However, a small training tactile data set does not allow covering the high intra-class variability. In this condition, traditional machine learning methods fail to construct a robust model from few samples. To tackle this challenging issues, we propose a transfer learning algorithms able to proficiently learn new task with few number of tactile data by relying on other previously learned models (past tactile knowledge or past experience). The proposed transfer learning algorithm is the extended and improved version of [6] and [7] from binary to multi-class transfer learning. Using the proposed transfer learning method, a robotic system can employ its previously learned multiple tactile models at while learning a new task.

II. SYSTEM DESCRIPTION

Multi-Modal Artificial Skin (BioTac): The BioTac is a multi-modal tactile sensor. When the sensor moves over an object, the generated vibration can be measured, amplified, and filtered to obtain a dynamic pressure signal ($\mathbf{P}_{AC}$) with the sampling data rate of 2 KHz. The BioTac also has 19 impedance-sensing electrodes ($\mathbf{E}_1, ..., \mathbf{E}_{19}$) distributed over the surface of the rigid part to measure the deformation that arises when normal forces are applied to the surface of the skin with a 50 Hz sampling data rate Fig.(1).

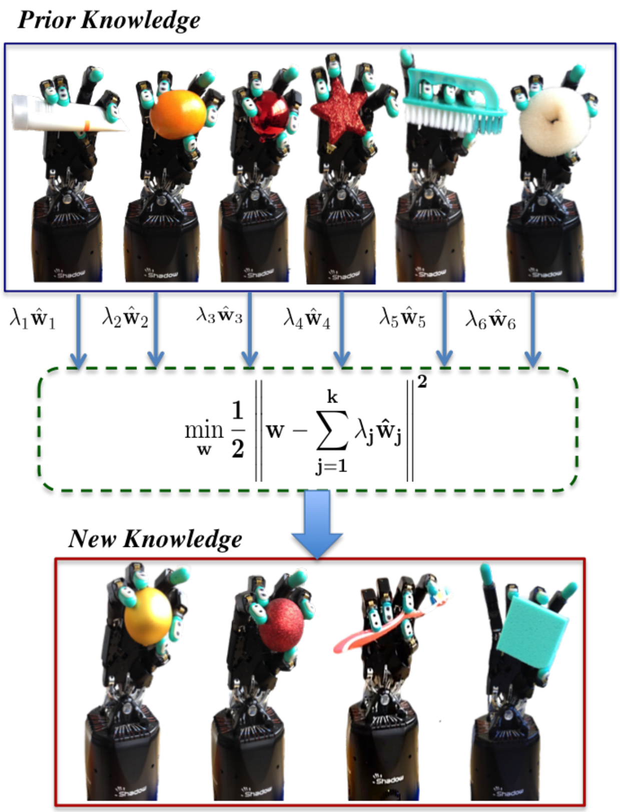

Fig. 1. The Shadow Dexterous Hand with BioTac Tactile Sensor-Employing the proposed tactile transfer learnig method enables the Shadow Hand to re-use its prior knowledge when descriminating new objects while having very few tactile data samples.

Shadow Dexterous Hand: The Shadow Hand is an advanced Robotic Hand System that provides up to 24 movements. The Shadow Hand is fully integrated via ROS to the BioTacs and the CyberGlove Fig.(1).

Cyber Gloves: The CyberGlove is a data glove that accurately captures the sophisticated movement of a user's fingers and hand. The Glove System provides an intuitive way to control the Shadow Hand Fig.(1).

III. Learning Methodology

The exploratory movement carried out by the Shadow Hand to obtain the relevant tactile data consisted of sliding a fingertip over the surface of the objects which were measured by the dynamic pressure sensor in the BioTac ($\mathbf{P}_{AC}$) and the impedance sensing electrode array ($\mathbf{E}_1, ..., \mathbf{E}_{19}$), respectively.

***Feature Extraction Techniques*:** We previously proposed a set of biologically-inspired feature descriptors [8]-[9]. The proposed descriptors represent the statistical properties of the vibro-tactile signals in the time domain, called *Activity*, *Mobility*, *Complexity*, *Pcorr*, and *Scorr*. The final feature descriptor includes computed mobility and complexity parameters from the output of the dynamic pressure sensor, each impedance sensing electrode and linear and non-linear correlation coefficient between each impedance sensing electrode output, and the dynamic pressure sensor. [$Mobility(P_{AC})$, $Mobility(E_K)$, $Complexity(P_{AC})$, $Complexity(E_K)$, $Pcorr(P_{AC}, E_K)$, $Scorr(P_{AC}, E_K)$]. Each calculated feature vector had 80 data points per trial.

$$Activity = Var(s(t)) = \frac{1}{N}\sum_{i=1}^{N}(S_i - \bar{S})^2 \tag{1}$$

$$Mobility = \sqrt{\frac{Var(\frac{ds(t)}{dt})}{Var(s(t))}} \tag{2}$$

$$Complexity = \frac{mobility(\frac{ds(t)}{dt})}{mobility(s(t))} \tag{3}$$

$$Pcorr(P_{AC}, E_K) = \frac{\sum_{i=1}^{N}(P_{AC_i} - \bar{P}_{AC}).(E_{K_i} - \bar{E}_K)}{\sqrt{\sigma(P_{AC}).\sigma(E_K)}} \tag{4}$$

$$Scorr(P_{AC}, E_K) = 1 - \frac{6\sum_{i=1}^{N}R_i^2}{N(N^2-1)} \tag{5}$$

Where N is the number of data points, K is the number of impedance electrodes and for the BioTac $K = 19$, and R_i is the difference between the rank of $(P_{AC})_i$ and the rank of $(E_K)_i$.

TABLE I

PROPOSED FEATURE DESCRIPTOR

[***Mobility*** , ***Complexity***, ***Pcorr***, ***Scorr***]

IV. Tactile Perception and Data Collection

***Exploratory Behavior*:** To generate human-like exploratory movements by the Shadow Dexterous Hand, the CyberGlove was used. A human user wearing the CyberGlove was asked to grasp an experimental object in-hand and then to explore the surface of the object by sliding a fingertip over it's surface.

***Properties Of Experimental Objects*:** In this study 10 everyday objects were selected including a Red and Yellow balls, a Rough textured ball, a Rough textured star, a Memory sponge, a Toothbrush, a Floor brush, a Spongy ball, an Orange, and a Cream tube (Fig.2).

***Data Collection*:** The CyberGlove was used to grasped each of the object by the Shadow Hand. The middle finger and the thumb of the Robotic Hand was used to slide **1** cm over the surface of the in-hand object to collect the training and test data set respectively.

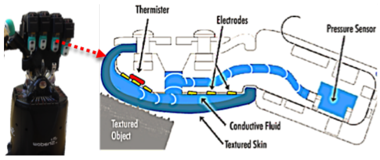

Fig. 2. Human-like exploratory movements generation by the Shadow Dexterous Hand.

V. *Robot Learning Methods*

***Expectation Maximization (EM)*:** The Expectation Maximization (EM) algorithm was employed to qualitatively differentiate between varying categories of objects through their texture properties. This means that objects having the same surface texture tend to be in the same cluster (unsupervised learning).

***Tactile Transfer Learning* :** In this experiment, the task of the Shadow Hand was to build up a prior knowledge model using six object presented in the upper row in Fig.(2) and then to re-use them as prior models to classify new objects from one or very few available training samples. Our proposed transfer learning technique is a developed and improved version of the presented methods in [6], [5].The method proposes a principle solution to evaluate automatically the relatedness among multiple prior models and the new target task. By employing this technique, the Shadow Hand can manage to construct texture models for the new target tasks on the basis of *very few number of training samples* using a reliable combination of six different prior models from minimizing the generalization error of the obtained new target model. A discriminating model for the new target task is then constructed with the condition of closeness to a combination of weighted priors knowledge models [6]. More formally, suppose there are k prior knowledge, each containing $\mathbf{N}_k$ samples as $(\mathbf{x}_\ell, y_\ell)$ $\ell = 1, \ldots, N_k$. A discriminating model is learned for each task in terms of a linear function $g_j(\mathbf{x}) = \hat{\mathbf{w}}_j \cdot \mathbf{x}$ $\quad j = 1, \ldots, k$. For a new target task with T available samples being in the same data space of the prior models $(\mathbf{x}_t, y_t)$ $t = 1, \ldots, T$, BTL solves the Eq.(6).

$$\min_{\mathbf{w},b} \frac{1}{2}\left\|\mathbf{w} - \sum_{j=1}^{k}\lambda_j \hat{\mathbf{w}}_j\right\|^2 + \frac{C}{2}\sum_{t=1}^{T}(y_\ell - \mathbf{w}\cdot\mathbf{x}_t - b)^2 \ . \tag{6}$$

The optimization problem Eq.(6) has the same cost function as LS-SVM [10] in which the regularizer term has been modified to impose closeness between the new target task model and a linear combination of prior models. The weights λ assigned to each prior knowledge are found by minimizing $\sum_{t=1}^{k}\ell_t(\tilde{y}_t, y_t)$ subject to $\|\lambda\|_2 \leq 1$ where $\tilde{y}_t$ is the leave on out (LOO) prediction for the t^{th} sample and $\lambda = (\lambda_1, \ldots, \lambda_k)$

With this formulation the final prediction function on the target task is

$$g(\mathbf{x}) = \mathbf{w} \cdot \mathbf{x} + b = \left(\sum_{j=1}^{k} \lambda_j \hat{\mathbf{w}}_j + \sum_{t=1}^{T} \alpha_t \mathbf{x}_t \right) \cdot \mathbf{x} + b \ . \quad (7)$$

In Eq.(7) α_t are the coefficients of the support vectors for the new target problem.

VI. Experimental Results

***Object Categorization Results*:** The EM algorithm was trained with the entire unsupervised collected data set. A class to clustering approach was used to evaluate how well the robotic hand can recognize the correct category of a novel test data. From the confusion matrix Fig.(3) is clear that many objects were confused with each other. For instance, the Rough textured star, Rough ball, Spongy ball, Tooth brush, and Floor brush are confused several times with each other which is due to having the similar surface textures. Moreover, the Cream tube, Orange, Red ball, and Yellow ball were also confused with each other since they have similar smooth surfaces.

Tactile Transfer Learning Approach : In order to classify four new objects in the lower row in Fig.(2) from one or very few training samples, first the LSSVM was trained with the entire collected data from six objects shown in the upper part of the Fig.(2) in order to build up prior tactile knowledge models for the Shadow Hand. In the next step, the Shadow Hand used the proposed method to discriminate four new objects (the Yellow ball, Rough ball, Tooth brush, and Memory Sponge) while employing only one training sample of the objects pulse prior tactile knowledge. In the next steps, the number of training samples incrementally increase one by one.

Baselines: To compare our experimental results the *Least Squared S upport Vector Machine (LSSVM)* [10] strategy has been employed. In this respect, first the LSSVM was trained with only one training sample from each of our objects shown in lower part of the Fig.(2). In the next steps, the number of the samples were increased incrementally to 10. Fig.(4) shows that the Shadow Hand managed to discriminate four in-hand objects with similar surface textures with 95% recognition accuracy rate. In this case the Shadow Hand employed only one training sample plus the prior knowledge. However, Fig.(4) illustrates that the Shadow Hand achieved 83% recognition accuracy while using the traditional learning to classify the same objects. By increasing the number of the training samples to 10 and while using the tactile transfer learning (prior knowledge), the Shadow Hand succeed to classify the objects with 100% recognition accuracy.

VII. Conclusion

In this study we proposed a new tactile transfer learning method in order to enable robotic systems to exploit their previous knowledge/experience while recognizing new objects from their surface properties. The experimental results show that using the proposed tactile transfer learning algorithm outperforms the traditional learning method especially when only one or few training samples are available.

Identified As (columns) / *Actual Object* (rows)

Objects	*Red ball*	*Yellow ball*	*Rough ball*	*Rough Star*	*Spongy ball*	*Floor brush*	*Tooth brush*	*Orange*	*Cream Tube*	*Memory sponge*
Red ball	7	1	0	0	0	0	0	1	1	0
Yellow ball	2	6	0	0	0	0	0	1	1	0
Rough ball	0	0	6	2	1	0	1	0	0	0
Rough star	0	0	2	6	1	0	0	0	0	1
Spongy ball	0	0	1	1	7	0	1	0	0	0
Floor brush	0	0	0	0	1	8	1	0	0	0
Tooth brush	0	0	1	1	1	0	7	0	0	1
Orange	0	0	0	0	0	0	0	8	2	0
Cream tube	1	1	0	0	0	0	0	0	8	0
Memory sponge	0	0	1	0	0	0	1	0	0	8

Fig. 3. Confusion matrix for EM unsupervise in-hand object clustering

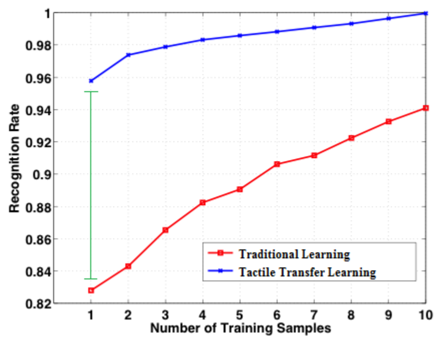

Fig. 4. In-hand object classification resultsby the Shadow Hand using traditional learning method and the proposed tactile transfer learning algorithm

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