Novel Tactile Descriptors and a Tactile Transfer Learning Technique for Active In-Hand Object Recognition via Texture Properties

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***Abstract*— This paper proposes robust tactile descriptors and ,for the first time, a novel online tactile transfer learning strategy for discriminating objects through surface texture properties via a robotic hand and an artificial robotic skin. Using the proposed tactile descriptors the robotic hand can extract robust tactile information from generated vibro-tactile signals during in-hand object exploration. Tactile transfer learning algorithm enables the robotic system to autonomously select and then exploit the previously learned multiple texture models when classifying new objects with a few training samples or even one. The experimental outcomes demonstrate that employing the proposed methods and 10 prior texture models, the robotic hand could identify 12 objects through their surface textures properties with 97% and 100% recognition rate respectively with only one and ten training samples.**

I. Introduction and Background

Tactile information is crucial for autonomous robots for detecting and learning the physical properties of objects. The performance of tactile systems depends not only on the technological aspect of the sensory device, but also on the design of the learning methods that interpret information contained in tactile data [1]. The object material can be characterized and differentiated based on surface texture, stiffness, and thermal information obtained through tactile sensing. However, to the best of our knowledge, so far there is no research paper addressing object discrimination via their physical properties while the objects are in the hand of a robot. Jamali *et al.* fabricated a biologically inspired artificial finger composed of silicon within which were two PVDF pressure sensors and two strain gauges. The finger was mounted on a robotic gripper and was scraped over eight materials. The Majority voting learning method was employed to find the optimal technique for the texture recognition problem [3]. Hu *et al.* used Support Vector Machine (SVM) to classify five different fabrics by sliding a finger-shaped sensor over the surfaces [4]. Dallaire *et al.* [5] managed to classify 28 different surfaces such as Aluminum, Plexiglas and Kitchen towel via Bayesian non-parametric learning approach. In this respect, a three axis accelerometer was placed on a stylus, which was then mounted above a rotating turn-table on which the surface was placed. Ten different surfaces were detected through an artificial neural network by sliding an accelerometer mounted prob over the surfaces such as wooden flooring, short hair carpet, and tile linoleum flooring [6]. Liu *et al.* employed an intelligent contact sensing finger to classify surface materials with Naive Bayes classifier [7]. Hu *et al.* used Support Vector Machine (SVM) to classify five different fabrics by sliding a finger-shaped sensor over the surfaces [4]. A robot actively knocks on the surface of the experimental objects with an accelerometer-equipped device to discriminate stone, mulch, moss, and grass from each other with a lookup table and k-nearest neighbors (K-NN) techniques [8]. A multi-modal tactile sensor called BioTac was used to perceive tactile information. In this experiment one BioTac sensor was placed on a customized tool and a vibration-free linear staged was used to slide textures under the tactile sensor. In [9], the Shadow Hand with the BioTac sensor on the index

Fig. 1. This figure shows the uniform in-hand objects considered as Prior Objects. The Shadow Hand with the BioTac sensors is exploring the texture properties of the in-hand objects with an identical shape. It moves any of the fingertips to slide over the objects surface and uses the proposed tactile descriptors to extract robust tactile information.

Fig. 2. This figure demenstrates the complex shape in-hand objects considered as New Objects. Employing the proposed tactile transfer learning the Shadow Hand discriminates new objects from their texture with a very few trials whilst re-using prior knowledge.

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fingertip and Bayesian exploration technique were employed to discriminate 10 different objects from each other by executing exploratory movements over the objects surface. However, the existing texture classification methods are not able to re-use the past experience or prior learned texture models (tactile transfer learning). The focus of this study is to propose a set of robust tactile feature descriptor for active in-hand object recognition via surface texture properties. For the first time in the community of the tactile object recognition, we propose an online tactile transfer learning method to enable robotic hands to re-use their prior tactile knowledge to discriminate new in-hand objects (through their textural properties) with a few available training samples or even one (one-shot tactile learning).

II. SYSTEM DESCRIPTION

A. *Robotic Hand*

The Shadow Hand is a dexterous Robotic Hand System with five fingers and 20 active degrees of freedom in total, which enables the robot to have a range of movement equivalent to that of a human hand (see Fig.1).

B. *Multi-Modal Artificial Skin*

The BioTac is a multi-modal tactile sensor. When the sensor moves over an object, caused vibration can be measured by a dynamic pressure signal ($\mathbf{P}_{AC}$) with the sampling data rate of 2 KHz. Moreover, BioTac has 19 impedance-sensing electrodes ($\mathbf{E}_1, ..., \mathbf{E}_{19}$) measuring the deformation that arises when normal forces are applied to the surface of the skin with a 50 Hz sampling rate (see Fig.1).

C. *Properties Of Experimental Objects*

In this work 22 everyday objects were selected. 10 objects with an identical geometrical shape including a Red and a Yellow ball with almost similar smooth surface texture, a Rough textured ball, an Orange, an apple, a Colorful ball with smooth and non-uniform texture, a Rough spherical sponge, a Pine apple textured ball, a String ball, and Mirror ball (see Fig.1-Prior Objects). Also, 12 objects with different shapes including a Soft Sponge, a Memory sponge (non-uniform texture), a Toothbrush (non-uniform texture), a Floor brush, a Rough textured star, a Soap, a Spray, a Coffee capsule, a Paper box, a Cream tube, a Plastic baby feeder, a Metal ruler (see Fig.2-New Objects).

D. *Data Collection With Prior Objects Set*

In this scenario, the Shadow Hand held each of the spherical shaped prior objects (see Fig.1-Prior Objects) in palm with three random fingers. Afterwards, the robotic hand explored the texture of each in-hand object by randomly moving the remaining free fingers (two fingers) over the surface of the object for 3 seconds. The texture exploration was repeated 50 times for each prior objects with random orientation. The collected tactile data for each object then randomly divided in tow sets, one with 30 samples for the training and the other one with 20 trials for the testing. Altogether, 300 training and 200 testing samples for 10 prior objects.

E. *Data Collection With New Objects Set*

In this case, the Shadow Hand used three fingers to hold each complex shaped object (Fig.2-New Objects). The exploration carried out with the remaining two fingers by sliding over the surface texture of the object for 3 seconds. The rest of data collection procedure remained as same as described before.

III. *Proposed Feature Descriptors*

The generated tactile signals were measured by pressure sensor ($\mathbf{P}_{AC}$) and the impedance sensing electrode array ($\mathbf{E}_1, ..., \mathbf{E}_{19}$). To extract robust information from vibro-tactile signals we propose a set of parameters, called *Activity*, *Mobility*, *Complexity*, linear correlation coefficient Eq.(4), and non-linear correlation coefficient Eq.(5) [10], [11].

$$Activity = \frac{1}{N}\sum_{n=1}^{N}(S_n - \bar{S})^2 \tag{1}$$

$$Mobility = \sqrt{\frac{Var(\frac{dS_n}{dn})}{Var(S_n)}} \tag{2}$$

$$Complexity = \frac{mobility(\frac{dS_n}{dn})}{mobility(S_n)} \tag{3}$$

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

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

where S_n is the input signal, N is the number of data points, K is the number of impedance electrodes, and R_i is the difference between the rank of $(P_{AC})_i$ and the rank of $(E_K)_i$.

IV. PROPOSED TACTILE TRANSFER LEARNING TECHNIQUE

Consider a scenario in which the Shadow Hand has already constructed a set of learning models to discriminate $k = 10$ different surface textures using Least Squared Support Vector Machine learning algorithm with sufficient available training samples (in our case 300 training samples) as well as high enough measured tactile information (tactile data collected by five fingertips). Now the new task of the Shadow Hand is to classify $N = 12$ new surface textures with one or a very few available training samples while re-using the prior texture models in an online manner.

1) ***Constructing Prior Tactile Models:*** LS-SVM was trained with k prior object textures (in our 10 objects Fig. 1-Prior Objects) to construct surface texture models as a prior knowledge . By slightly modifying the regularization term in LS-SVM, it is possible to construct new discriminating texture models for the new objects (see Fig.2-New Objects) close to the already constructed prior models.

*2) **Prior Tactile Knowledge Selection**:* Suppose there are already $k = 10$ constructed models, and N new object textures with T available training samples for each new object textures $(\mathbf{x}_t, y_t)$ $t = 1, \ldots, T$. The optimization problem has the same cost function as LS-SVM in which the regularize term has been modified to impose closeness between the new object texture models and a linear combination of prior models.

*3) **Online Tactile Transfer Learning**:* The proposed online tactile transfer learning in [12] is a hybrid algorithm which integrates the prior and new models via the adapted version of LS-SVM in order to properly initialize the PA algorithm (see Algorithm 1). $\mathbf{w}_1$ is composed of two parts. The first part is the linear combination of the weighted prior models where $\mathbf{w}_s$ is the prior model, λ_s is the scaling factor, and k is the number of prior models. The second part represents the received new training samples in which T is the number of the samples. Now, the PA algorithm uses the new initial models $\mathbf{w}_1$ instead of the $\mathbf{w}_1 = (0, \ldots, 0)$ to learn from the $(t+1)-th$ new incoming samples. So far, we initialized the PA leaning algorithm by integrating the prior and new models. But, still, the prior models are not directly re-weighted during the on-line learning process. We describe here how during the on-line learning progressively update the prior and new models weights in time. In this case, the prediction can be made on each new incoming samples by means of the current constructed models (see Algorithm 1) as $\mathbf{w}_1 \cdot \mathbf{x}_t$. The results of the prediction $\sigma_{k,t}$ will be cropped between -1 and 1 and will be used as the $(d+k)-th$ element in the feature vector descriptor of $\mathbf{x}_t$.

Algorithm 1 : Proposed Online Tactile Transfer Learning

For $t = 1$

Initialize PA: $\mathbf{w}'_{k,1} = (\mathbf{w}_1, \mathbf{1}) \in \mathbb{R}^{d+k}$ *where*

where $\mathbf{w}_1 = (\sum_{s=1}^{k} \lambda_s \hat{\mathbf{w}}_s + \sum_{t=1}^{T} \alpha_i \mathbf{x}_i)$

For $t = 1, 2, ..., T$ $T = 10$

Input to PA: $\mathbf{x}_t$ *New Comming Samples*

$\mathbf{x}'_t = (\mathbf{x}_t, \sigma_{1,t}, \ldots, \sigma_{k,t}) \in \mathbb{R}^{d+k}$, $\eta = 1$

Augmented Samples

where: $\sigma_{k,t} = \max\{-1, \min\{1, \mathbf{w}_{k,1} \cdot \mathbf{x}_t\}\} \Rightarrow \sigma_{k,t} \in [-1, 1]$

- **Prediction:** $\hat{y}_t = sign(\mathbf{w}'_{k,t} \cdot \mathbf{x}'_t)$
- **Suffer loss:** $\ell_t = max\{0, 1 - y_t \mathbf{w}'_{k,t} \cdot \mathbf{x}'_t\}$
- **update:**

1.set $\theta_t = \min\left\{\eta, \frac{max\{\ell_t\}}{\|\mathbf{x}'_t\|^2}\right\}$

2.update: $\mathbf{w}'_{k,t+1} = \mathbf{w}'_{k,t} + \theta_t y_t \mathbf{x}'_t$

V. Experimental Results

A. *Constructing Prior Tactile Model*

In order to build up a 10 prior models with the collected training samples during the prior object textures exploration the LS-SVM classifier was employed. The entire training samples (30 training samples for each prior texture and all together 300 training samples) were split in to parts, 70% for training and 30% for the test. Five-fold cross validation was applied in order to find the optimal kernel parameter and regularizer value C. LS-SVM was re-trained with entire collected training data and the optimal found parameters to construct 10 prior leaning models. The learning models $(\mathbf{w}, \mathbf{b}) \in R^{10}$ were evaluated by predicting on unseen collected test data (20 test samples for each class of prior texture and altogether 200). The LS-SVM could manage to classify successfully 10 prior textures with 100% recognition accuracy.

B. *Evaluation of proposed Online Transfer Learning*

In this experiment, the Shadow Hand used the proposed tactile transfer learning technique to recognize 12 new surface textures while re-using ten $k = 10$ already learned prior models together with learning from a very few training samples. In this scenario, the collected training samples (see Fig.2-New Objects) during new textures exploration entered to the proposed hybrid online transfer learning sequentially one after one to construct new hybrid learning models. At each time $t = 1, ..., 10$, the constructed leaning models were evaluated by predicting on unseen test data collected during the new object textures exploration (20 test samples per new textures). The prediction results were reported as a recognition rate in Fig. 3.

C. *Baseline*

In order to compare our obtained results the traditional PA algorithm was employed to construct surface texture models while receiving new training samples continuously over time (one new texture per time t ($t = 1, \cdots, 10$)). The new constructed learning models at each time t were evaluated by predicting on unseen test data (20 test samples per new textures). The classification results were reported as a recognition rate in Fig. 3. The value for η was fixed to 1 in both hybrid online transfer learning and PA online leaning (base line). Fig. 3 shows that using our proposed hybrid online transfer learning method the Shadow Hand could discriminate 12 new texture with 97% recognition accuracy while using only one training sample plus 10 prior models. By increasing the number of training samples from one to ten, the Shadow Hand achieved 100% recognition accuracy. The results in Fig. 3 illustrates that our proposed method outperforms the traditional online learning. Although the PA achieved lower classification accuracy compare to the proposed methods, PA achieved 78% and 97% recognition accuracy while learning from one and ten training samples respectively. The obtained high classification performance by PA is due to the fact that our proposed feature descriptors provided the PA algorithm with information-rich tactile data.

*1) **Negative Knowledge Transfer Consistency**:* In transfer learning scenario the constructed prior models are not always relevant for new object models. If the prior models are dissimilar to the new models, brute force transfer can degrade the recognition performance generating so called negative knowledge transfer. Ideally, a transfer learning method should be beneficial between prior and new models while avoiding negative transfer when the object surface textures are not a good match. We show that our proposed tactile transfer learning technique is robust against of the negative knowledge transfer. In this respect, Expectation Maximization algorithm was employed to find out which of the new object textures are similar or dissimilar to the prior textures. In this case, the EM was trained with entire training samples (10 samples per each texture) to cluster all available 20 objects (both prior and new object textures). The EM then was evaluated by unseen test data (20 samples per each texture). In this scenario, Spray, Metal ruler, Pine apple, and String ball were selected as a set of new textures while the prior textures were remain same. The hybrid online transfer learning was employed to discriminate the four new textures and traditional PA was used as a base line. The procedure was the same as describe above. Fig. 4 shows the classification results in terms of recognition accuracy. The illustrated results clearly shows that the obtained recognition performance while using the proposed hybrid online transfer learning is similar to the performance achieved while using the traditional PA. This means that our algorithm stopped transferring irrelevant prior knowledge to new task (see Fig. 4).

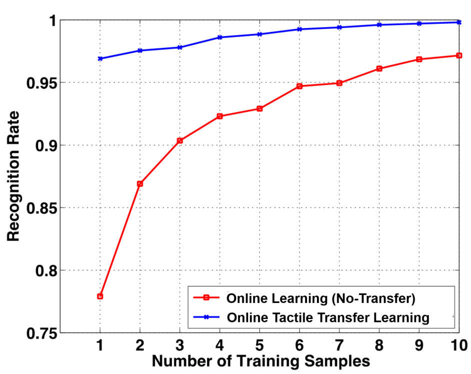

Fig. 3. This figure shows the recognition results on a separate test data for the online tactile transfer learning and traditional PA online learning (No-Transfer) methods. In this experiments 10 prior models were re-used by the Shadow Hand as prior tactile knowledge.

VI. Conclusion

We proposed robust tactile descriptors for active in-hand object recognition task. Furthermore, for the first time, we designed an online tactile transfer learning methods to provide the robotic systems with the ability of re-using previously learned tactile models (prior models) to discriminate new in-hand objects with a very few available

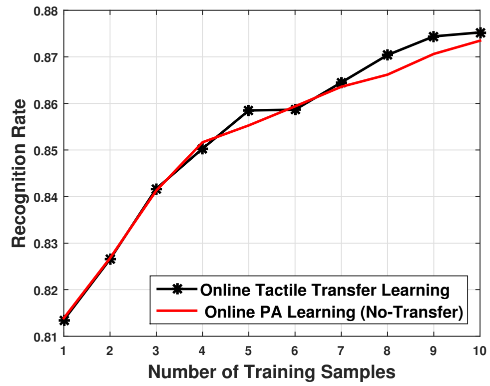

Fig. 4. This figure shows the recognition results corresponding to hybrid tactile transfer learning and traditional transfer learning (No-Transfer) in which the new surface textures were dissimiar to the prior textures. The recognition results on the test set were plotted as a function of the number of the trainig samples

training samples. In this study, the distributions of the tactile information in both prior knowledge and new tasks were similar.

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References

[1] M. Kaboli, A. Long, and G. Cheng, "Humanoids learn touch modalities identification via multi-modal robotic skin and robust tactile descriptors," *Journal of Advanced Robotics*, (In Press), 2015.

[2] N. Jamali and C. Sammut, "Majority voting: Material classification by tactile sensing using surface texture," *IEEE Transactions on Robotics*, vol. 27, pp. 508–521, June 2011.

[3] 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*, vol. 14, pp. 4899–4913, 2014.

[4] P. Dallaire, P. Giguère, D. Émond, and B. Chaib-draa, "Autonomous tactile perception: A combined improved sensing and bayesian non-parametric approach," *Robotics and Autonomous Systems*, vol. 6, no. 4, pp. 422–435, 2014.

[5] P. Giguere and G. Dudek, "A simple tactile probe for surface identification by mobile robots," *IEEE Transactions on Robotics*, vol. 27, pp. 534–544, June 2011.

[6] H. Liu, X. Song, J. Bimbo, L. Seneviratne, and K. Althoefer, "Surface material recognition through haptic exploration using an intelligent contact sensing finger," *IEEE International Conference on Intelligent Robots and Systems*, pp. 152–57, 2012.

[7] J. Windau and W. Shen, "An inertia-based surface identification system," *IEEE International Conference on Robotics and Automation*, pp. 2330–2335, 2010.

[8] D. Xu, G. E. Loeb, and A. J. Fishel, "Tactile identification of objects using bayesian exploration," in *IEEE International Conference on Robotics and Automation*, pp. 3056–3061, May 2013.

[9] M. Kaboli, P. Mittendorfer, V. Hugel, and G. Cheng, "Humanoids learn object properties from robust tactile feature descriptors via multi-modal artificial skin," *IEEE-RAS International Conference on Humanoid Robots*, pp. 187–192, Nov 2014.

[10] M. Kaboli, T. D. L. 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*, pp. 1155–1160, 2015.

[11] 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*, 2016.