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In-Hand Object Recognition via Texture Properties with Robotic Hands, Artificial Skin, and Novel Tactile Descriptors

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***Abstract*— This paper, for the first time, proposes a solution for the problem of in-hand object recognition via surface textures. In this study, a robotic hand with an artificial skin on the fingertips was employed to explore the texture properties of various objects. This was conducted via the small sliding movements of the fingertips of the robot over the object surface as a human does. Using our proposed robust tactile descriptors, the robotic system is capable of extracting information-rich data from the raw tactile signals. These features then assist learning algorithms in the construction of robust object discrimination models. The experimental results show that the robotic hand distinguished between different in-hand objects through their texture properties (regardless of the shape of the in-hand objects) with an average recognition rate of 97% and 87% while employing SVM and PA as an online learning algorithm, respectively.**

Fig. 1. The Shadow Hand 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.

I. INTRODUCTION

A. *Motivation*

The human body is covered with skin, which provides us with the sense of touch. Thousands of cutaneous receptors inside of the skin, as well as proprioceptive sensors in joints and muscles, assist us to perceive the ambient world, inferring the physical properties of objects through hand-object interactions. Based on this ability, future robots are envisioned to have a sound haptic system like humans. To achieve this goal, many roboticists have focused their efforts on advancing tactile sensor technology in the last few decade [1]–[5]. However, in contrast to the rapid progress of tactile sensors, the research in processing and learning tactile information is still in the early stage.

B. *Background*

Previously, researchers simply employed customized tools or robotic end-effectors equipped with various technological tactile sensors to classify objects via their materials. 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 [6]. Hu *et al.* used Support Vector Machine (SVM) to classify five different fabrics by sliding a finger-shaped sensor over the surfaces [7]. 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) [8]. Different kinds of paper have been identified by Principle Component Analysis (PCA) technique during pushing and sliding of tactile sensor on the paper. To classify cotton, linen, silk, and denim fabrics, Song *et al.* designed a mechanism to generate the relative motion at a certain speed between the PVDF film and surface of the perceived fabric. In this study neural network and K-means clustering algorithms were used for fabric surface texture recognition [9]. Dallaire *et al.* [10] 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 [11]. A humanoid robot was equipped with an artificial finger

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nail with an attached 3-axis accelerometer in order to classify 20 different surfaces through Support Vector Machine (SVM) and k-nearest neighbor (k-NN) learning techniques. To do this the fingernail was used to scratch the surfaces. Faster scratch usually turned out to have a higher recognition accuracy. Additionally, combination of multiple scratches was more accurate than a single scratch [12]. In order to classify 117 textures, one BioTac sensor was placed on a customized tool and a vibration-free linear staged [13]. The index finger of Shadow Hand having a BioTac sensor was employed to discriminate 10 different objects [14]. In this study, the base and wrist of the robotic hand were fixed on a table. Moreover, all joints in the hand and wrist were deactivated (except 2 joints of the index finger).

C. *Contribution*

In contrast to the previous works, the focus of this paper is that of in-hand object recognition through texture properties. In this scenario, an anthropomorphic hand with an artificial skin on fingertips was employed. The robotic hand explored the texture properties of the in-hand objects while moving any of fingertips to slide over the surface of the in-hand objects, as human does. Using our proposed novel tactile descriptors, the robotic hand extracted high-informative features from the perceived tactile data to construct discriminative texture models for the task of in-hand object classification.

II. SYSTEM DESCRIPTION

A. *Robotic Skin*

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

B. *Robotic Hand*

The Shadow Hand[2] is an advanced Robotic Hand System with five fingers and 20 active degrees of freedom in total. This enables the robot to have a range of movement equivalent to that of a human hand (see Fig. 1).

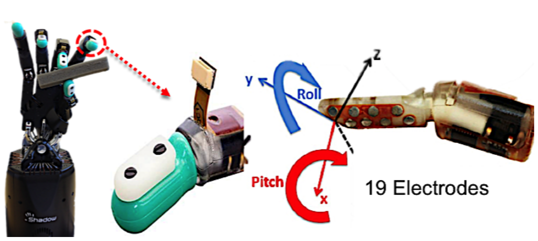

Fig. 2. The Shadow Robotic Hand is equipped with the BioTac sensors on each fingrtip.

[1]http://www.syntouchllc.com/
[2]http://www.shadowrobot.com/

III. TACTILE PERCEPTION AND DATA COLLECTION

Humans can discriminate in-hand objects by perceiving texture properties (without consideration of the shape of the objects) whilst moving any of the fingertips to slide over the surface of the objects.

A. *Experimental Objects Properties*

In this work 20 everyday objects were selected. 10 objects with an identical geometrical shape property (in this case a spherical shape), including a Red and Yellow balls with almost same smooth surface texture, a Rough textured ball, an Orange, an Apple, a Colorful ball with smooth surface, a Rough spherical sponge, a Pine ball and a String ball (both with an irregular texture), and a Mirror ball (see Fig. 1). Also, 10 objects with different complex shapes, including a Soft sponge, a Memory sponge, a Toothbrush, a Floor brush, a Rough textured star, a Nespresso coffee capsule, a Spray, a Paper box, a Cream tube, and a Plastic baby feeder (see Fig. 3). In both set of objects, the difference in the texture properties varied from relatively similar to noticeably different.

Fig. 3. The Shadow Hand is exploring the texture properties of the in-hand objects with complex shapes. It moves any of the fingertips to slide over the objects surface.

B. *Data Collection*

Training Data Collection: The Shadow Hand held each of the objects with three fingers including thumb, small, and ring finger. In order to perceive the texture properties of each in-hand object, the robotic hand used its index and middle fingers to slide over the surface of the object for 2 seconds. The sensory data was measured by the BioTac using each of the 19 electrodes ($\mathbf{E}_1, ..., \mathbf{E}_{19}$) and the pressure sensor ($\mathbf{P}_{AC}$) (in total 40 tactile signals from the output of two BioTac sensors). The entire procedure was repeated 10 times for each experimental object.

Test Data Collection: In this case, the robotic Hand used the small, ring, and middle fingers to keep the objects in hand. The thumb and index finger were used to explore the texture properties of each experimental object. The rest of the procedures were the same as described for the training data collection. However, the exploratory behavior was repeated 20 times for each of the experimental object.

C. *Feature Extraction Techniques*

The human-like exploratory/sliding movements carried out by the Shadow Hand to perceive the relevant tactile data about the texture properties of in-hand objects. The exploratory motion generated two types of tactile data which were measured by the pressure sensor $(\mathbf{P}_{AC})$ (with 2 KHz sampling rate) and the impedance sensing electrode array $(\mathbf{E}_1,...,\mathbf{E}_{19})$ (with 50 Hz sampling rate). In order to design robust tactile descriptors, we considered the tactile information measured by the pressure sensor corresponded to high-frequency texture information. In addition, we assumed that the tactile data sensed by the impedance sensing electrodes was related to the lower frequency changes in the textures. These two types of tactile data provide information especially about non-uniform or transitional periods in the overall structure.

D. *Pre-Processing*

Before computing the feature descriptors, pre-processing of each signal was required. In this respect the mean value of each obtained signal during exploratory behavior (for 2 second) was subtracted with the original raw signal (zero mean) to maximize useful information and minimize the effect of artifacts.

E. *Proposed Feature Descriptors*

In the earlier works, researchers employed the Fourier transform technique [13], [14] to interpret the obtained tactile information for texture classification. However, the Fourier transform is not appropriate for analyzing non-stationary signals in which textures are irregular or non-uniform. Short time Fourier transform or Wavelet might be the most appropriate techniques to analyze non-stationary signals [15], [16]. However, these methods deal with a large number of data points, thereby causing difficulties at the classification step. More features require more training samples resulting in the growth of the computational complexity as well as the risk of over-fitting. To overcome these issues, in [17] and [18], we proposed a set of fundamental tactile descriptor inspired by Hjorth parameters [19]. In this study, we used the fundamental parameters to construct a new set of robust feature descriptor. These parameters are called *Activity*, *Mobility*, and *Complexity*. Although these parameters are defined in the time domain, they can be interpreted in the frequency domain as well. The first parameter (1) is the total power of the signal. It is also the surface of the power spectrum in the frequency domain (Parseval's relation). The *Mobility* parameter, defined in (2), is determined as the square root of the ratio of the variance of the first derivative of the signal to that of the signal. This parameter is proportional to standard deviation of the power spectrum. It is an estimate of the mean frequency [20]. The last parameter in (3) gives an estimate of the bandwidth of the signal, which indicates the similarity of the shape of the signal to a pure sine wave. Since the calculation of the Hjorth parameters is based on variance, the computational cost of this method is sufficiently low, which makes them appropriate for the real-time task.

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

$$Mobility = \sqrt{\frac{Var\Big(\frac{dS(n)}{dn}\Big)}{Var\Big(S(n)\Big)}} \qquad (2)$$

$$Complexity = \frac{mobility\Big(\frac{dS(n)}{dn}\Big)}{mobility\Big(S(n)\Big)} \qquad (3)$$

where $S(n)$ is the input signal either impedance electrodes $(\mathbf{E}_1,...,\mathbf{E}_{19})$ or the the pressure sensor signal $(\mathbf{P}_{AC})$ during 2 seconds exploratory movements. N is the number of the data sample. For $(\mathbf{P}_{AC})$ with 2 KHz sampling rate N = 4000 and for each electrode array $(\mathbf{E}_1,...,\mathbf{E}_{19})$ with 50 Hz sampling rate, N=100.

Furthermore, when the fingers of the Shadow Hand came into contact with the surface of an object, the change in fluid pressure of the artificial skin linearly correlated with the output of the impedance sensing electrodes. However, when the fingertips were sliding, the relationship between the electrode array and fluid pressure was no longer linear and was monotonically related to each other in a non-linear manner. Therefore, both linear correlation coefficient Eq.(4) and non-linear correlation coefficient Eq.(5) between impedance-sensing electrodes and dynamic pressure sensor were considered as tactile feature data:

$$Pcorr(P_{AC},E_k) = \frac{\sum_{n=1}^{N}\Big((P_{AC})_n - \bar{P}_{AC}\Big).\Big((E_k)_n - \bar{E}_k\Big)}{\sqrt{\sigma(P_{AC}).\sigma(E_k)}} \qquad (4)$$

$$Scorr(P_{AC},E_k) = 1 - \frac{6\sum_{n=1}^{N}\Big(R_k\Big)_n^2}{N(N^2-1)} \qquad (5)$$

where N is the number of data points, $K = 19$ is the number of impedance electrodes (for the BioTac $k = 1,...,19$), and R_k is the difference between the rank of (P_{AC}) and the rank of (E_k).

***Final Feature Descriptors*:** The total feature descriptors for one finger include the computed Activity, complexity, and complexity of the output of the dynamic pressure sensor $(\mathbf{P}_{AC})$, mean value of the Activity, complexity, and complexity of each impedance sensing electrode $(\mathbf{E}_1,...,\mathbf{E}_{19})$ and the mean value of the linear and non-linear correlation coefficient between each impedance sensing electrode, and the dynamic pressure sensor. Each calculated feature vector had 8 data points per trial sample defines as

$$\Big[Activity(\mathbf{P}_{AC}), Complexity(\mathbf{P}_{AC}), Mobility(\mathbf{P}_{AC}),$$
$$\frac{1}{K}\sum_{k=1}^{K} Activity(\mathbf{E}_k), \frac{1}{K}\sum_{k=1}^{K} Complexity(\mathbf{E}_k),$$
$$\frac{1}{K}\sum_{k=1}^{K} Mobility(\mathbf{E}_k), \frac{1}{K}\sum_{k=1}^{K} Pcorr(\mathbf{P}_{AC}, \mathbf{E}_k),$$
$$\frac{1}{K}\sum_{k=1}^{K} Scorr(\mathbf{P}_{AC}, \mathbf{E}_k)\Big] \quad (6)$$

The final proposed feature descriptor was the concatenation of the total descriptors (6) of the two fingers, index and middle fingers for the training and thumb and index fingers for the testing data collection. Each calculated final feature vector had 16 data points per each trial sample.

IV. *Robot Learning Methodologies*

Support Vector Machine (SVM): The first common learning method that was evaluated was Support Vector Machine (SVM). More formally, given labeled training data (supervised learning), the algorithm constructs a hyper-plane or set of hyper-planes in a high dimensional space in order to classify new examples.

Passive Aggressive Online Learning (PA): In this study the Passive Aggressive (PA) online learning algorithm was employed. The PA is a margin based online or open-ended learning technique with low computational complexity compare to the batch learning algorithms. PA continuously constructs and updates the learning models. The constructed learning models, at each time step, are used to generate the corresponding prediction for the current received samples. The received true labels are then used as a feedback to update the learning models for the upcoming coming new samples.

Expectation Maximization (EM): The Expectation Maximization (EM) algorithm was employed to categorize objects via their textures. EM is an unsupervised and iterative algorithm that generalizes k-means to a probabilistic setting in two steps. The Expectation step computes the cluster probability of each data sample and the Maximization step uses these probabilities to estimate the distribution parameters. Since there is no supervised training step, an initial model needs to be construct with a random set of parameters. After the model is initialized, EM optimizes the set of parameters until it finds a local maximum of log-likelihood. Convergence is ensured since the algorithm is guaranteed to increase the log-likelihood at each iteration.

V. RESULTS

A. *Object Classification Results By SVM*

Identical Shape Objects: The SVM classifier and the linear kernel method was used to discriminate the identical-shape objects through surface texture properties (see Fig. 1). In order to obtain the best regularizer value, C, for SVM, 5-fold cross validation (CV) was used. In this respect, the collected training data set was randomly split into 5 folds and during each evaluation, 4 of those were used for training and one was used for testing. This procedure was repeated 10 times to obtain an average performance on the evaluation sets. The entire process was repeated 20 times using different values for C to find the one with the lowest CV error. The SVM with optimal parameters was then re-trained on entire training data set to construct the learning models. The constructed learning models were used by the Shadow Hand to predict on the unseen separately collected test set. In this scenario, the Shadow Hand successfully classified the objects via their texture properties with 97% recognition accuracy, substantially higher than the chance classifier. Fig. 4 shows the confusion matrix obtained from the classification procedure. The confusion matrix indicates how often a given object or surface was miss-classified as another object/surface. Perfect classification would result in a diagonally-filled table. However, Fig. 4 shows that most errors involve objects with similar surface texture properties. For instance, the Yellow ball was confused with the Red and Colorful ball as they have very smooth surface textures. Moreover, the Rough ball was identified as the Spongy ball since both objects share almost identical texture properties.

Complex Shape Objects: The Shadow Hand employed SVM with linear kernel method to discriminate complex shape objects through texture properties (see Fig. 3). The optimal regularizer value was obtained from 5-fold cross validation, the detailed procedure of which has been explained above. The classifier was trained with the training data set of the complex shape objects. The constructed learning models were used to predict the surface textures of the objects in the testing data set. In this case, the Shadow Robotic Hand achieved 97.5% classification accuracy. Regarding to the confusion matrix (see Fig. 5), the Spray and the Coffee capsule were confused with each other as they have similar material properties. The confusion matrix also shows that in one trial the Rough star was miss-classified as the Toothbrush. These two objects are sharing similar texture properties.

Complex and Identical Shape Objects : The Shadow Hand used the SVM to classify all 20 objects in Fig. 1) and Fig. 3) via their surface textures without consideration of their geometrical properties. The SVM with the best regularizer value was trained with the entire combined collected training data. The constructed object models were then evaluated by predicting on the combined testing set. The Shadow Hand successfully discriminated 20 multiple shape objects with 96% recognition accuracy. The confusion matrix (see Fig. 6) illustrates that the classification of the objects through surface texture properties depends only on the texture properties of the objects. It means that a robotic system can discriminate objects via their texture properties without considering the visual and geometrical information about the objects. The performance of the object classification depends only on how well and accurate the robotic system can perceive and interpret the texture properties of the objects.

[2]This technique is known as a PAI [21].

Identified As

Actual Object	Red ball	Yellow ball	Rough ball	Orange	Apple	Colorful ball	Spongy ball	Pine ball	String ball	Mirror ball
Red ball	20	0	0	0	0	0	0	0	0	0
Yellow ball	1	18	0	0	0	1	0	0	0	0
Rough ball	0	0	18	0	0	0	2	0	0	0
Orange	0	0	0	20	0	0	0	0	0	0
Apple	0	0	0	0	20	0	0	0	0	0
Colorful ball	0	0	0	0	0	20	0	0	0	0
Spongy ball	0	0	1	0	0	0	19	0	0	0
Pine ball	0	0	0	0	0	0	0	20	0	0
String ball	0	0	0	0	0	0	0	0	20	0
Mirror ball	1	0	0	0	0	0	0	0	0	19

Fig. 4. Confusion Matrix For SVM Classification of The Identical Shape Objects.

Identified As

Actual Object	Soft sponge	Memory Sponge	Tooth brush	Floor brush	Rough star	Coffee capsule	Spray	Paper Box	Cream tube	Baby feeder
Soft Sponge	20	0	0	0	0	0	0	0	0	0
Memory Sponge	0	20	0	0	0	0	0	0	0	0
Tooth brush	0	0	19	0	1	0	0	0	0	0
Floor brush	0	0	0	20	0	0	0	0	0	0
Rough star	0	0	1	0	19	0	0	0	0	0
Coffee capsule	0	0	0	0	0	19	1	0	0	0
Spray	0	0	0	0	0	1	19	0	0	0
Paper Box	0	0	0	0	0	0	0	20	0	0
Cream tube	0	0	0	0	0	0	0	0	20	0
Baby feeder	0	0	0	0	0	0	0	0	1	19

Fig. 5. Confusion Matrix For SVM Classification of The Complex Shape Objects.

Identified As

Actual Object	Red ball	Yellow ball	Rough ball	Orange	Apple	Colorful ball	Spongy ball	Pine ball	String ball	Mirror ball	Soft sponge	Memory Sponge	Tooth brush	Floor brush	Rough star	Coffee capsule	Spray	Paper Box	Cream tube	Baby feeder
Red ball	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Yellow ball	1	17	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Rough ball	0	0	18	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
Orange	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Apple	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Colorful ball	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Spongy ball	0	0	1	0	0	0	18	0	0	0	0	0	0	0	1	0	0	0	0	0
Pine ball	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0
String ball	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0
Mirror ball	1	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0
Soft Sponge	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0
Memory Sponge	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0
Tooth brush	0	0	0	0	0	0	0	0	0	0	0	0	19	0	1	0	0	0	0	0
Floor brush	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0
Rough star	0	0	1	0	0	0	1	0	0	0	0	0	1	0	17	0	0	0	0	0
Coffee capsule	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	1	0	0	0
Spray	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	19	0	0	0
Paper Box	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0
Cream tube	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0
Baby feeder	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	18

Fig. 6. Confusion Matrix For SVM Classification of All 20 Objects.

B. *Object Classification Results Using PA*

The Shadow Robotic Hand used PA algorithm as an online learning approach in order to construct surface texture models whilst receiving training samples over time (one sample of each object per time t). In this experiment, the value for C was fixed to 1. The training data set was provided sequentially. The recognition rates at each time t was computed by applying the currently trained models on the test data ($t = 1, \cdots, 10$). The above procedure was applied on the collected training data with multiple shape objects. The constructed learning models was then evaluated by predicting on the testing data collected with the identical shape, complex shape, and multiple shape objects, separately. Fig. 7 shows the classification accuracy rate corresponding to *Identical Shape Objects*, *Complex Shape Objects*, and *Multiple Shape Objects*. By looking at the obtained results, it is obvious that the Shadow Hand was able to recognize identical, complex, and multiple shape objects via surface textures with high average recognition rate substantially better than chance. The Shadow Hand obtained an average recognition rate of 87% at $t = 10$ while only 10 data samples were used to train the algorithm. In this experiment, using PA method together with our proposed feature descriptors which provide the information-rich tactile feature, enabled the Shadow Hand to achieve high recognition rates in all scenarios. The obtained results are comparable with the ones that the Shadow Hand achieved with SVM. However, the Shadow Hand paid less computational cost while using the online learning algorithm.

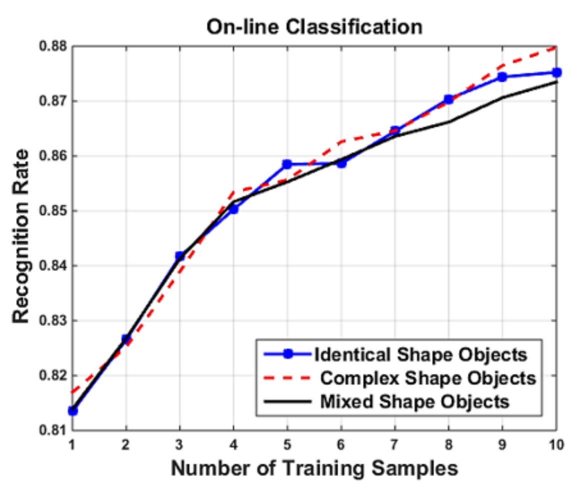

Fig. 7. On-line Classification Results For Identical-Shap Objects, Complex-Shape Object, and Multiple Shape Objects (Identical + Complex)-Shape Pbjects usin PA online classifier

C. *Object Categorization Using EM*

In this experiment, the robotic hand employed the EM algorithm as an unsupervised learning approach to categorize objects through their texture properties. In this respect, the EM was trained with the entire unsupervised data set. A class to clustering approach was used to evaluate how well the Shadow Hand can recognize the correct category of a novel test data. In this approach, classes were assigned to the categories, based on the majority value of the class attribute within each categories. Later on, these assignments were used to compute the classification performance. Fig. 8 shows the results of this experiment for the identical shape objects, complex shape objects, and multiple shape objects individually. From Fig. 8, it is clear that the Shadow Hand successfully categorized identical shape objects via surface texture with the accuracy of 82.23%. Using the EM and similar learning procedure as above the Shadow Hand also clustered the complex shape objects and multiple shape objects with the accuracy of 83.5%, and 80.58%, respectively.

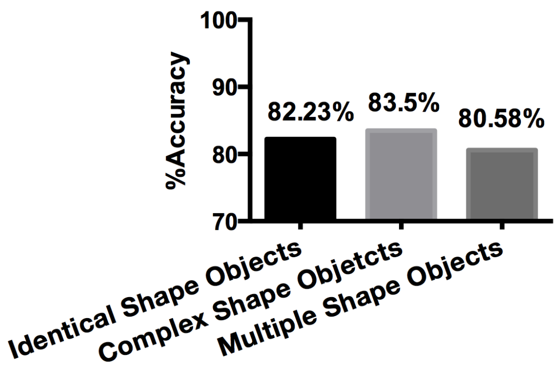

Fig. 8. Categorization Results Of The Identical Shape Objects, Complex Shape Objects, and Multiple Shape Objects.

VI. CONCLUSION

This study contributes three key improvements on existing systems; in-hand object exploration, invariance to the specific finger used for data collection, and ability to classify regardless of object shape. A range of simplistic learning techniques were applied, and consistently very high classification accuracy were observed for all objects across all learning methods. This result is a reflection of the high-information content of the proposed feature descriptors. As a future work it is interesting to evaluate the efficiency and robustness of our proposed technique with the other existing robotic hands specially when the robotic hands generate random exploratory movements.

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