3-D shape recognition using soft robotic hand based on flex sensor values

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***Abstract*—This paper details the 3-D shape recognition by the bend of flex sensors for objects in different shapes, using soft robotic hand with flex sensors. The major challenge of object classification is how to extract discriminative features from objects of different and similar shapes using values read from flex sensors. The proposed approach defines a new set of salient patterns. Driven by the proposed salient patterns, the geometric features are extracted and then concatenated and further incorporated into a machine learning framework to perform object recognition classification. The proposed approach is compared for five objects with binary classification techniques. We measured its accuracy and precision with experiments. We demonstrated its capability of grasping various kinds of regular objects.**

***Key Words* —Object classification. Flex sensors.**

I. INTRODUCTION

The human hand is not only a useful general-purpose manipulator, but a valuable perceptual system, as well. The human hand system is capable of fast and accurate object recognition. This paper presents a model and an implementation of a 3-D shape object recognition [1-2] by the degree of bend of the flex sensors. It mainly focuses on the classification of five different objects of different shapes. The system has been implemented on a soft robotic hand consisting of five flex sensors embedded to a glove on five fingers [3]. The sensors have been connected to Arduino board, with resistance of 65 kilo ohms each. Once data has been collected with the help of flex sensors for different people, binary classification techniques: KNN, SVM and neural networks have been applied to compare the accuracy and precision against different objects. Considering the above, the focus of this study was to, create a data set by collecting data using the flex sensors and perform basic binary classification which act as a baseline for future study and research.

II. 3-D SHAPE RECOGNITION SYSTEM

We identified the research area for our project of gesture recognition which relies on wearable sensor technologies like data gloves using flex sensors [4-5]. Most wearable sensor systems for gesture recognition are gloves embedded with sensors [6]. In most research endeavors, gloves are custom Built [7-9].

2.1 Interaction oriented and natural hand gestures-based recognition

As described in the introduction, we are interested in 3-D shape recognition based on the hand movements of the user. The novelty of system is to recognize the shape depends on the difference in the touch points for different shapes [10]. We worked and collected our data for 5 different shapes (Figure 1). At first, we collected the data only for open fist and closed fist and checked the touch points. In later phases, we allowed user to perform free actions with all the five objects in a fixed interval of time.

2.2 Custom Data Glove

The touch points vary for different shapes. Some shapes have same touch points for all the 5 fingers whereas for some other shapes only 2-3 fingers will have significant touch points. We designed a glove with flex sensors that emphasis on detection of touch points of the fingers [11-13]. The glove is as depicted in (Figure 2). We placed one flex sensor on each finger of the glove. The sensor measures the bending value (which translates to voltage change) of the finger when user performs some action with an object and provides the voltage change for each finger. For recording the significant voltage change with the bending of flex sensors, we used resistance of 65 kilo ohms in our circuit. All the sensors are connected to Arduino board to collect the data and save the data for further processing. Our custom glove is a hardware prototype and as such it has some limitations mainly regarding usability. For long term wearing, glove should be made of more comfortable material, with smaller electronic components, should be available in different sizes and be wirelessly connected to the computing unit for more accurate data collection [14].

Figure 1: Objects with 5 different shapes

Figure 2: Glove embedded with flex sensors

3. Data Collection Experiment

We collected data of the participants for random actions for all the five objects in time interval of 20 seconds.

3.1 Participants

We collected data for 10 participants, 4 females and 6 males and participants were aged between 24-30 years. However, data can be collected from more participants for more than 5 objects to achieve better results. Due to time constraints, this study has been limited to smaller number of participants and objects.

3.2 Procedure

Before starting the experiment, participants were briefed about the purpose and process of the experiment (Figure 3). A time window of 20 seconds was set, and a counter was set up to monitor the time. For each record, following steps were performed in sequence:

1. Participant was provided with one shape.
2. A counter was set up for 20 seconds.
3. On start of counter, the data record was start for collecting data through tool called ***"Cool Term".***
4. Participant performed some random action with the object in the time frame.
5. The recording was stopped at 20 seconds.
6. All the data was labelled with name of participant and shape of image.

Every action was performed twice and for any error, data was re-collected from the same participants in the same time frame.

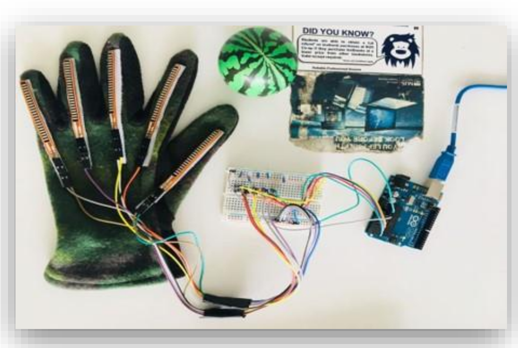

Figure 3: Over all setup of glove and circuit

4. Algorithmic design

In this section we described the selection of algorithm and optimum configuration for the best results we get for our experiment. We experimented using raw data and then filtered the data to compare against three algorithms and plotted the results for visualization.

4.1 Data pre-processing

Since, the data collected through the tool has few rows with 0 or missing values due to lose connection of the sensor with the glove. The data was cleaned, and missing values were replaced with average value [15] of above and below the corresponding rows of the data set. This step is performed only for raw data and then the normalization technique has been applied.

4.2 Window length

For our data we obtained 5 columns each corresponding to a flex sensor voltage value and several rows (corresponding to time frame). Since data was collected for 20 seconds, the number of rows across all the data sets has been NOT consistent as different participants can perform various actions. Some rows at the start and end of the file were trimmed to bring the row count same for all the files.

4.3 Feature Engineering

The recorded data set contains [204X5] data matrix for each file with number of columns corresponding to A1, A2, A3, A4 and A5 which is 5 flex sensors corresponding to five fingers of glove and number of rows corresponding to time frame. Since the voltage value is different for each flex sensor, we normalize the value for the data for each file before further processing and files are saved for further processing.

sklearn.preprocessing.MinMaxScaler(feature_range=(0, 1*))*

MinMax scalar transforms features by scaling each feature to a given range. This estimator scales and translates each feature individually such that it is in the given range on the training set, e.g. between zero and one.

We visualized the normalized data by plotting the histogram [16] for each finger for each object as shown in figure 4.1 to 4.9. Also, we plot a histogram for trend of each flex sensor data value and histogram for value increase, decrease or no change (compared to next row value) is recorded.

4.4 Algorithmic selection

Since the focus of this study to collect the data and to invite people for further research on 3-D object recognition, we selected the binary classification algorithms and checked the accuracy of the existing system in object recognition. As observed from the study of work of other people [17-19], classification algorithms have proven to provide robust performance on activity recognition using wearable sensors, namely: K Nearest Neighbours (KNN), Support Vector Machine (SVM), Neural Networks (NN) [19,20].

Support Vector Machine is one of the supervised Machine Learning Technique, used for classification and regression; it belongs to generalized linear classifiers. SVM is a mostly used method in pattern recognition and object recognition. The objective of the support vector machine is to form a hyperplane as the decision surface in such a way that the margin of separation between positive and negative examples is maximized by utilizing optimization approach.

In pattern recognition, the k-nearest neighbour algorithm [21] (k-NN) is a method for classifying objects based on closest training examples in the feature space. The k-nearest neighbour algorithm is amongst the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbours (k is a positive integer, typically small). If k= 1, then the object is simply assigned to class of its nearest neighbour. The nearest-neighbour method is perhaps the simplest of all algorithms for predicting the class of a test example.

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Histograms for different objects

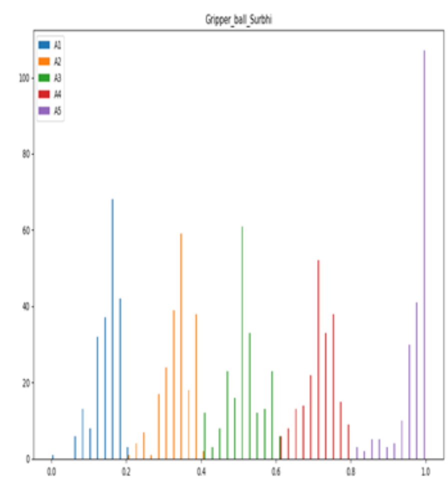

Figure 4.1 Gripper ball_1

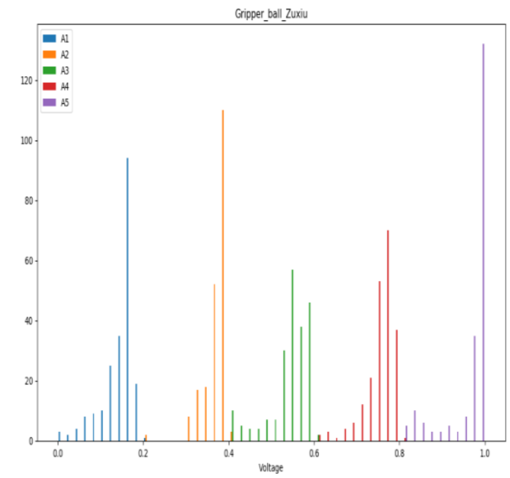

Figure 4.2 Gripper ball_2

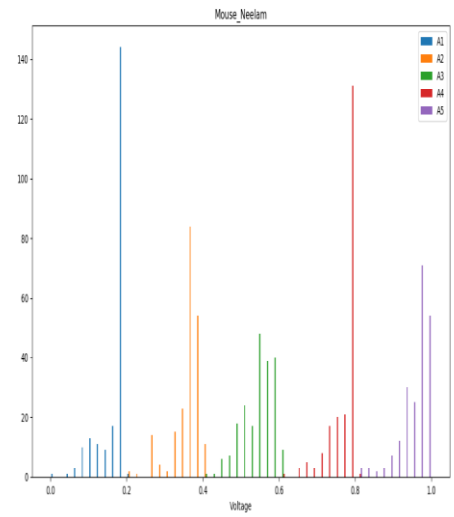

Figure 4.3 Object Mouse_1

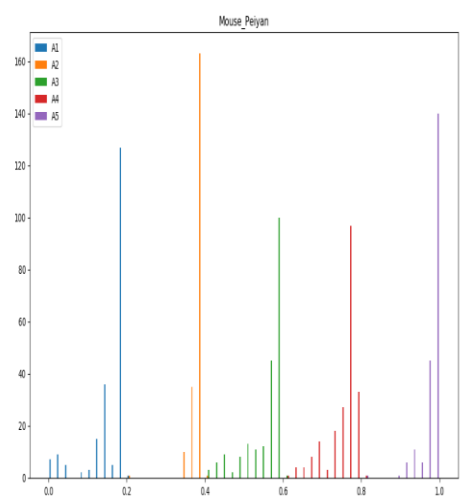

Figure 4.4 Object Mouse_2

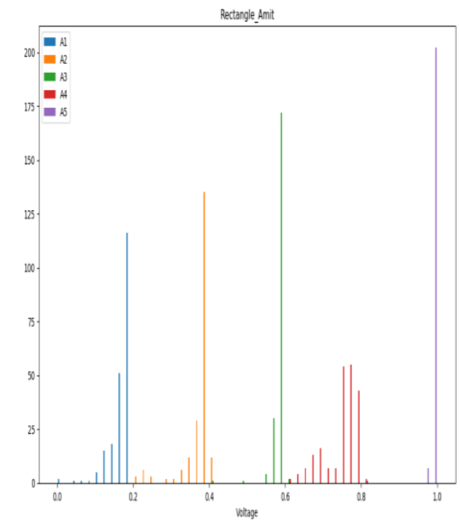

Figure 4.5 Object Rectangle_1

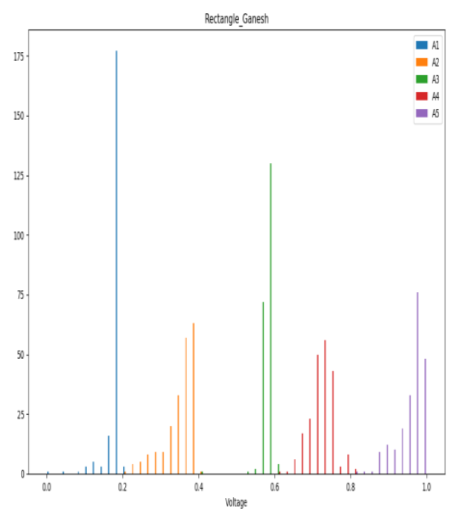

Figure 4.6 Object Rectangle_2

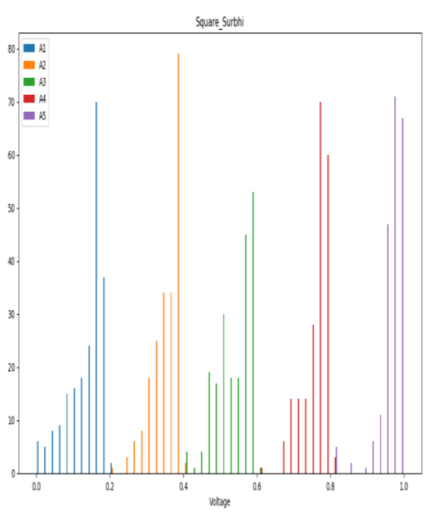

Figure 4.7 Object Square_1

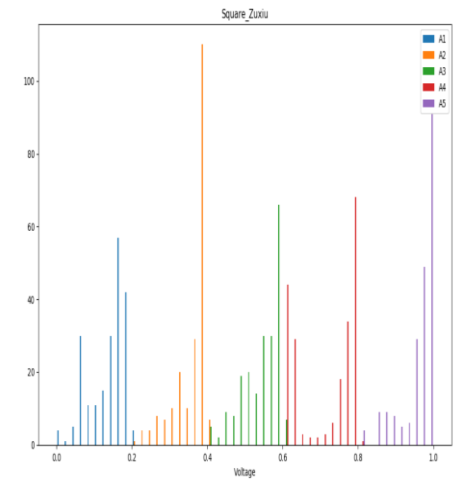

Figure 4.8 Object Square_2

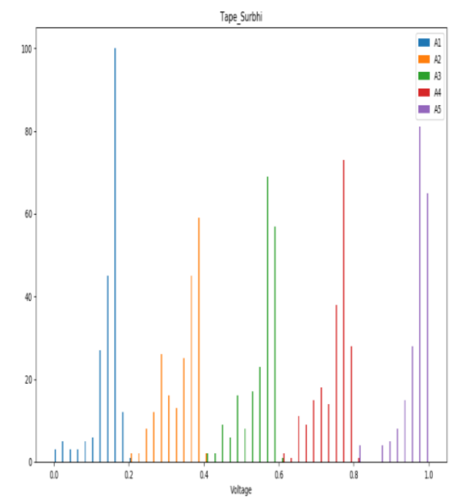

Figure 4.8 Object Tape_1

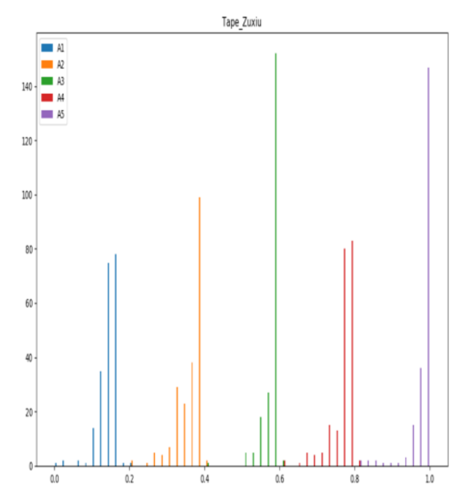

Figure 4.9 Object Tape_2

5. Algorithm Evaluation

In this section we report on accuracy and precision (Table 2) on the full dataset for the selected algorithm and configuration. Models are trained in the ratio of 60:40 i.e. train: test. All the data set is used for measuring the performance with different binary classification algorithms. We apply KNN, SVM and Neural networks (NN) on the data set and generated a confusion matrix (Table 1) using Scikit-learn for further analysis [22-23].

Confusion matrix also known as error matrix is a specific table layout that allows visualization of the performance of an algorithm. Each row of a matrix represents the instance in an actual class which each column represents the instance in a predicted class. If a classification system has been trained to distinguish between different objects, a confusion matrix will summarize the results of testing the algorithm for further inspection. In predictive analytics, a table of confusion matrix, is a table with two rows and two columns that reports the number of false positives, false negatives, true positives, and true negatives. This allows more detailed analysis than mere proportion of correct classifications (accuracy).

Confusion matrix is given below against multiple objects can be predicted in this way with number of true positives vs true negatives and false positives vs false negatives.

	predicted		
actual		negative	positive
	negative	TN True positive	FP False Positive
	positive	FN False negative	TP True positive

Mouse vs Rectangle	SVM confusion matrix [[538 299] [87 716]] KNN confusion matrix [[760 77] [56 747]] NN confusion matrix [[578 259] [114 689]]
Mouse vs Square	SVM confusion matrix [[666 171] [503 300]] KNN confusion matrix [[733 104] [145 658]] NN confusion matrix [[533 304] [242 561]]
Mouse vs Tape	SVM confusion matrix [[751 86] [48 755]] KNN confusion matrix [[807 30] [7 796]] NN confusion matrix [[771 66] [62 741]]
Square vs Tape	SVM confusion matrix [[723 114] [82 721]] KNN confusion matrix [[808 29] [7 796]] NN confusion matrix [[740 97] [92 711]]
Square vs Rectangle	SVM confusion matrix [[480 357] [120 683]] KNN confusion matrix [[751 86] [49 754]] NN confusion matrix [[575 262] [156 647]]
Rectangle vs Tape	SVM confusion matrix [[766 71] [41 762]] KNN confusion matrix [[815 22] [13 790]] NN confusion matrix [[792 45] [13 790]]

Table 1: Confusion Matrix

	Objects	**SVM**	**KNN**	**NN**
Accuracy and Precision	Mouse vs Rectangle	0.764 0.705	0.918 0.909	0.772 0.726
	Mouse vs Square	0.589 0.636	0.848 0.863	0.667 0.648
	Mouse vs Tape	0.918 0.897	0.977 0.963	0.921 0.918
	Square vs Tape	0.880 0.863	0.978 0.964	0.884 0.879
	Square vs Rectangle	0.709 0.656	0.917 0.897	0.745 0.711
	Rectangle vs Tape	0.931 0.914	0.978 0.972	0.964 0.946

Table 2: Binary classification algorithm results

As our results reveal, we achieve a high classification accuracy in general against few objects. From table we can predict that the accuracy between ***Mouse vs Tape*** object achieved high result. Results for other objects would have been more better and accurate if the data sets are large. It is important to stress that our results were achieved by including in the test set with the random actions performed by user on the object. In a live gesture recognition system, there is no way of excluding them. More specifically, in a live scenario, we don't know how a user is going to pick the object and the way he is going to hold the object.

In the end, it is important how fast the recognition system identifies the action performed by the user and then correctly recognizing the object being held.

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