Evaluation of Feature Representation and Machine Learning Methods in Grasp Stability Learning

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***Abstract*— This paper addresses the problem of sensor-based grasping under uncertainty, specifically, the on-line estimation of grasp stability. We show that machine learning approaches can to some extent detect grasp stability from haptic pressure and finger joint information. Using data from both simulations and two real robotic hands, the paper compares different feature representations and machine learning methods to evaluate their performance in determining the grasp stability. A boosting classifier was found to perform the best of the methods tested.**

I. INTRODUCTION

Grasping a known object in a known environment with a known robotic hand is a tractable problem. But immediately, when some of the facts are unknown, usually true in humanoid robot environments, the problem becomes much more difficult to solve. The problem studied here is how to estimate grasp stability when only haptic information is available. For example, in service robotics the models of objects are usually unknown and must be constructed from e.g. vision. Thus, there is no explicit object model, but the system is learning from haptic images of stable and unstable grasps. We show that it is possible to some extent to recognize when a grasp is stable when given only the haptic pressure and finger joint information.

A number of different sensor modalities can be used to deal with the uncertainty from having an unknown object during grasp. With sensors, we can determine when the object is in contact with the hand, giving additional information besides the kinematic configuration of the hand. Tactile sensors are useful here, as they measure the force or pressure inflicted on the sensor matrix, giving the area of the contact as well as the total force.

To determine the grasp stability, the stability criteria must be linked to the haptic data. This can be done either analytically or through learning. In this paper, we study the use of learning for grasp stability evaluation where a system learns the measure of stability based on a number of examples. Through an experimental study, our aim is to assess the suitability of different feature representations and machine learning methods in the problem of learning grasp stability from haptic input. The focus of the study is to evaluate the grasp stability from a single haptic data instance using both discriminitive and generative classifiers and different feature representations from data-driven dimensionality reduction techniques to application specific feature extraction methods. The approach taken in this paper gives the benefit of detecting whether the grasp is stable or unstable at any instant during grasping knowing neither perfect object information nor the hand kinematics. The approach is also generalizable to any configuration of tactile sensors in the hand which are able to measure pressure level. Both simulated and real data is used to determine the differences and similarities when comparing simulation with real platforms.

The paper is divided into six sections: Section II is a study of related work in the area of the paper, Section III introduces the different features for the classification, Section IV describes the machine learning algorithms used in the experiments and Section V contains the actual performed experiments. Finally Section VI concludes the paper with discussion and future work.

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II. RELATED WORK

Grasp stability analysis by analytical means is a well established field. However, to analytically determine the grasp stability, the kinematic configuration of the hand and the contacts between the hand and the object must be perfectly known. Previous studies on this subject are numerous and [1] gives a detailed review. However, the references are useful only in cases when conditions described above are true. When this is the case, it is possible to determine if the grasp is either force or form closure grasp [2], which ensures the stability. Compared to this body of work, we wish to learn the stability from existing data, i.e. the tactile data.

While there is currently little work directly comparable to our work, many have studied the use of tactile and other sensors in a grasping context. Felip and Morales [3] developed a robust grasp primitive, which tries to find a suitable grasp for an unknown object after a few initial grasp attempts. However, only finger force sensors were used in the study.

Apart from using tactile information as a feedback for low level control [4], tactile sensors can be used to detect or identify object properties. Jiméneza et al. [5] use the tactile sensor feedback to determine what kind of a surface the object has, which is then used to determine a suitable grasp for an object. Petrovskaya et al. [6] on the other hand use tactile information to reduce the uncertainty of the object pose, upon an initial contact with the object. In their work, a particle filter is used to estimate object's pose, but the tactile sensor used to detect contact with the object is not embedded in the gripper performing the grasping.

Object identification has been studied by Schneider et al. [7] and Schöpfer et al. [8] Schneider et al. show that it is possible to identify an object using tactile sensors on a parallel jaw gripper. The approach is very similar to object recognition from images and the object must be grasped several times before accurate recognition rates are achieved. Schöpfer et al. use a tactile sensor pad instead of a gripper or a hand which could be used to grasp the object. [8] is a study on different temporal features which can be used to recognize objects. Similar object recognition systems have been presented in [9], [10].

Preliminary results using the method presented in this paper have been published in [11]. However, this paper takes a significantly broader look into different classifiers and feature reprentations. Learning the grasp stability from examples provides a good ground to cope with the uncertainty in the process generally not studied in the case of analytic approaches.

III. FEATURE REPRESENTATIONS

A haptic data instance, $\mathbf{H} = [\mathbf{t}\ \mathbf{j}]$, consists of the tactile readings, $\mathbf{t}$, and of the grasp joint configuration, $\mathbf{j}$. Depending on the hand used, the dimensionality of both $\mathbf{t}$ and $\mathbf{j}$ changes. In this study, three different platforms are used:

- Simulated Schunk Dextrous Hand (SDH), 3 fingers each with 12x6 tactile elements, $\mathbf{t} \in \mathbb{R}^{216}$, $\mathbf{j} \in \mathbb{R}^{7}$
- Schunk Dextrous Hand, 3 fingers each with 13x6 tactile elements (Weiss tactile sensors), $\mathbf{t} \in \mathbb{R}^{234}$, $\mathbf{j} \in \mathbb{R}^{7}$
- Parallel Jaw Gripper, PG70, 2 fingers each with 14x6 tactile elements (Weiss tactile sensors), $\mathbf{t} \in \mathbb{R}^{168}$, $\mathbf{j} \in \mathbb{R}^{1}$

The dimensionality of $\mathbf{H}$ ranges from $\mathbb{R}^{169}$ to $\mathbb{R}^{241}$ with the listed platforms. The number of features in $\mathbf{H}$ can be considered large and potentially redundant. Thus, an effective method to reduce the dimensionality precedes the subsequent processing. Rest of the section describes the methods that are used to achieve this.

To provide an overview of the effect features have on the classification of the grasp stability, several types of feature representations are studied for training and classification. The features, denoted by $\mathbf{f}$, are derived from the tactile sensor data, $\mathbf{t}$. The features represent a variety of approaches from pure data-driven dimensionality reduction to application specific features. The features are computed from the tactile readings only while the joint configuration is used as is as a part of the haptic features.

A. Principal Component Analysis

Principal component analysis (PCA) is commonly used linear technique for dimensionality reduction. Here, PCA is computed using the covariance of the haptic data, $\mathbf{H}_{1,\ldots,n}$ and the resulting eigenvectors and eigenvalues,

$$C = cov(H_{1,\ldots,n}) , \qquad (1)$$

$$V^{-1}CV = D . \qquad (2)$$

Here, V represent the eigenvectors and D the corresponding eigenvalues. We chose the eigenvectors with the largest eigenvalues that combined explain 90% of the data. This results in ~ 60 eigenvectors.

B. Image Moments

Raw image moments are defined as

$$m_{p,q} = \sum_x \sum_y x^p y^q f(x,y) . \qquad (3)$$

The moments are computed up to order two, that is $(p+q) = o,\ \ o = \{0,1,2\}$, These are related to the total pressure, the mean of the contact area, and the shape of the contact area, indicated by the variance in x- and y-axes. Moments are computed for all tactile sensors individually, thus $\mathbf{f} \in \mathbb{R}^{18}$.

Raw image moments are used in the experiments as normalized image moments did not produce better results. This observation might be due to the fact that, e.g. rotation invariant moments, are not useful for grasp stability learning, as each grasp is unique.

C. Histogram

Histogram representation on the tactile data represents binning of the force affecting each cell of the tactile matrix. This operation also removes all spatial information. Thus, the histogram only considers the distribution of the affecting force. Using 10 histogram bins, $\mathbf{f} \in \mathbb{R}^{10}$.

D. Spatial Partitioning

Spatial partitioning partitions the area of the sensor matrix and sums the affecting force in every cell of the sensor matrix in each of these partitions. In essence, this subsamples the tactile image of each sensor matrix. Partitioning can be thought as opposite to the histogram operation, as partitioning retains the spatial information but loses some information of the force distribution. In the experiments, a 2x2 grid is used to partition the tactile image on each sensor, $\mathbf{f} \in \mathbb{R}^{12}$.

E. Local Binary Pattern

Local binary patterns (LBPs) [12] are used commonly for texture classification but also on face recognition. As its name suggests, local binary pattern codes local changes in a binary code. The local changes are found by thresholding the pixel neighbourhood by the value of the center pixel and checking which pixels are above the threshold. These binary codes are then added to a histogram, which is the final feature representing the original data. Images from all sensors are coalesced into one image and the LBP is applied to this image in the experiments. In the experiments, LBP produces a histogram where $\mathbf{f} \in \mathbb{R}^{59}$.

F. Row and Column Sums

Row and column sums is another form of spatial feature representation, where the colums and rows are summed independent of each other, thus, the resulting dimensionality of the feature representation is the sum of the tactile sensor dimensions, $i + j$, for each sensor,

$$sum_{c_i} = \sum_j t_{ij} \ , \tag{4}$$

$$sum_{r_j} = \sum_i t_{ij} \ , \tag{5}$$

where sum_{c_i} denotes the individual sensor columns and sum_{r_j} denotes the sensor rows.

IV. CLASSIFIERS

From a classification point of view, the problem of classifying grasp stability may be modelled as a classical two-class problem. Thus, the stability is classified as either stable or unstable. This is possible to implement with most of the basic classifiers without extending the theories behind them.

In the work presented here, a number of classifiers have been selected for the experiments. All the classifiers described represent different types of machine learning algorithms that help to understand the underlaying problem in grasp stability classification. In particular, we study both discriminative and generative approaches for classification.

A. Support Vector Machine

As the problem of grasp stability is binary, support vector machine (SVM) classification [13], [14] is suitable for the problem. Thus, here the focus is on the 2-class SVM. SVM is a maximum margin classifier, i.e. the classifier fits the decision boundary so that maximum margin between the classes is achieved. This guarantees that the generalization ability between the classes is not lost during the training of the SVM classifier.

Another feature of the SVM is the ability to use non-linear classifiers instead of the original linear hyper-plane classifier. Non-linearity is achieved using different kernels and in this study radial basis function (RBF) is used as the kernel for SVM:

$$K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2}, \quad for \quad \gamma > 0, \tag{6}$$

In addition to the parameter γ, constant C, related to the penalty applied to incorrectly classified training samples [13], needs to be set. The parameters can be found by searching the parameter space to find the optimal values. In this study, as an extension to the basic two-class SVM, probabilistic outputs for SVM by Platt [15] are used to analyze the results given by the SVM. The implementation of the SVM is by Chang and Lin [16].

B. Gaussian Mixture Model Classifier

As the naive Bayes classifier assumes that the data is distributed according to some modelable distribution, it is not optimal in cases where this assumption is not true. The haptic data is distributed according to an unknown distribution, thus it is reasonable to use Gaussian mixture model (GMM) statistical classifier.

While GMM methods assume a Gaussian distribution, GMM uses multiple Gaussian distributions to model the data which enables the methods to model multi-modal and more complex data. The implementation used in the experiments is by Paalanen and Kämäräinen [17].

TABLE I

TABLE OF PARAMETERS FOR FEATURES.

Features	Parameter	Parameter
Raw	-	-
PCA	-	-
Histogram	No. bins: 10	-
LBP	Uniform LBP	Samples: 8,1
Moments	-	-
Partitioning	Grid: 2x2	-
R&C sums	-	-

C. k-Nearest Neighbour

k-nearest neighbour [18] classifier is a very simple algorithm to implement. This classifier requires no training phase, instead during the classification phase, the test samples are compared to all given training samples. The test sample is classified as the class with the most neighboring, i.e. closest, training samples. The k denotes the number neighbouring training samples that are used in the classification phase. k-nearest neighbour also has a proven [18] error rate that is no worse than two times the error rate of an optimal classifier when the amount of data approaches infinity.

D. AdaBoost

AdaBoost or adaptive boosting is a meta-algorithm for learning which was developed by Freund and Schapire [19]. Adaboost uses multiple weak classifiers, such as linear hyperplane classifiers, to classify the given training data. AdaBoost has a good generalization ability, however AdaBoost is not effective when outliers are present in the training data.

The AdaBoost-algorithm that is used in this study is based on a decision tree classifier with a variable branching factor. With a branching factor of 1, the tree classifier represents a linear hyperplane classifier. The implementation is by Vezhnevets [20].

V. EXPERIMENTS

The goal of the experiments is to study the effect of the presented features in conjunction with multiple different classifier methods. A number of different datasets with different assumptions are used in the experiments to determine what type of data is suitable for classification.

A. Experimental Setup

The parameters for features and classifiers are shown in tables I and II. The raw data from the tactile sensors is also used as features in addition to the features presented in Section III. The parameters were found by a parameter search across reasonable parameter space. Schunk Dextrous Hand hardware and objects used in the grasping experiments are shown in Figure 1.

The following datasets have been chosen from simulated data, which were generated using simulated SDH hand model in a simulation environment described in [21]:

- D_1, a cylinder, grasps sampled from the side
- D_2, a bottle, grasps sampled from the side
- D_3, a bottle, grasps sampled from the top
- D_4, a cylinder, grasps sampled from a sphere

TABLE II

TABLE OF PARAMETERS FOR CLASSIFIERS.

Classifier	Parameter	Parameter
SVM	C: 0.4	γ: 0.03
GMM	max. clusters: 19	max. error: 0.016
KNN	k: 3	-
AdaBoost	Branch factor: 1	-

- D_5, a bottle, grasps sampled from a sphere

The datasets $D_{1,2,3}$ represent cases where we know the pose of the object with some accuracy, and can plan for a grasp. The datasets $D_{4,5}$ are simulating situations where the position of the object is known to some extent but the orientation is highly uncertain, thus, the grasps are sampled from a sphere around the object. In the simulated data, the grasp stability computation is based on [22], but instead of one convex hull W, two convex hulls, W_f and W_τ are used to separate wrench space with respect to forces and torques, and additional constraints are placed on W_f, so that

$$\alpha(m \cdot \mathbf{g}) \in W_f \; , \alpha = 1.1 \; . \tag{7}$$

This allows the grasp to remain stable even if some additional forces are introduced in addition to the gravity. Datasets generated with real hands are following:

- D_6, a cylinder, grasps sampled from the side, SDH
- D_7, a bottle, grasps sampled from the side, SDH
- D_8, a bottle, grasps sampled from the top, SDH
- D_9, a box, grasps sampled from the side, PG70
- D_{10}, a shampoo bottle, grasps sampled from the side, PG70
- D_{11}, a shampoo bottle, grasps sampled from the top, PG70

Datasets $D_{6,\cdots,11}$ represent cases where an estimate of the object's pose is known, for example, from a vision system. This estimate is commonly noisy and thus we added the noise to the hand pose. The objects in datasets $D_{6,7,8,9}$ are rigid and the objects in datasets D_{10} and D_{11} are non-rigid, i.e. the objects are deformable. The grasp stability in these datasets was determined by grasping an object. In datasets $D_{6,\cdots,8}$ the object was rotated $[-120°, +120°]$ around the approach direction and in datasets $D_{9,\dots,11}$, the object was lifted and rotated $+90°$ around X and Y axes, where Z axis is the direction of lift. If the object moved independently of the hand, the grasp was unstable, otherwise it was stable.

The method used to evaluate the performance of the classifiers was 10-fold cross validation. The dataset sample size for each of the given datasets are shown in Table III with the maximum classification rate summarized from Tables IV and V. The sample size shown in the table is balanced, so that each dataset has equal amount of stable and unstable grasp samples. All other features were normalized to zero-mean and unit variance, except the raw features which were normalized to range $[0, 1]$. The normalization parameters were obtained from the training set and applied to both training and test sets.

TABLE III

DATASET SAMPLE SIZES AND CLASSIFICATION RATES.

Dataset	Sample size	Max. classification rate
D_1	6400	77.0%
D_2	4906	61.4%
D_3	4446	62.7%
D_4	5302	80.4%
D_5	8990	70.5%
D_6	140	92.1%
D_7	100	92.1%
D_8	50	84.6%
D_9	148	74.6%
D_{10}	148	59.0%
D_{11}	100	64.0%

B. Experimental Results

Result matrix with the described datasets is given in Table IV and Table V. The table shows the classification rate of each dataset with the indicated feature and classifier combination. Each row shows the best classifier in **bold** font and worst in *italic* font. The best and worst classifiers were determined on a 95 % confidence interval using the Agresti-Coull interval which approximates the binomial confidence interval. Multiple classifiers are deemed best if there is no statistically significant difference in the classification performance between them. Some results for GMM are omitted because of the training sample size requirements, thus, results for datasets $D_{6,\dots,11}$ are not shown.

The results in Tables IV and V show that there is a distinctive performance difference between the datasets. Simulated datasets, D_1 and D_4 perform usually better than the other simulated datasets. This performance gap is caused, at least partially, by the hand configuration, which allows the object to touch other areas of the hand where there are no sensors. This removes some of the important information about the object to be used in determining the grasp stability. Thus, it is important to set up the grasp sequence in a way that allows the sensored part of the hand to grasp the object.

This procedure is evident in the dataset gathered from the real hands, especially sets $D_{6,7,8}$, where the classification performance is above 75 % in some cases. However, the object in the datasets were rigid, which is not the case in sets $D_{10,11}$. These sets show mostly poor performance, indicating that further samples must be used to learn the grasp stability.

The best overall classifier is AdaBoost, which performs the best out of the four classifiers, while SVM is close second. Worst classifier is GMM, partially due to the extensive amount of data needed to train GMM successfully with some of the chosen features. Low amount of data available in datasets $D_{6,\dots,11}$ makes it difficult to determine within the 0.95 confidence interval the best classifier, but looking at the results, AdaBoost has the highest mean in these cases. SVM has some anomalies, these are suspected to be caused by the parameter and feature combinations, and could be fixed by adjusting the parameters of SVM.

C. Feature Study

To study the effect of the features on the classification rate, tests with a 3-nearest neighbour classifier were conducted on

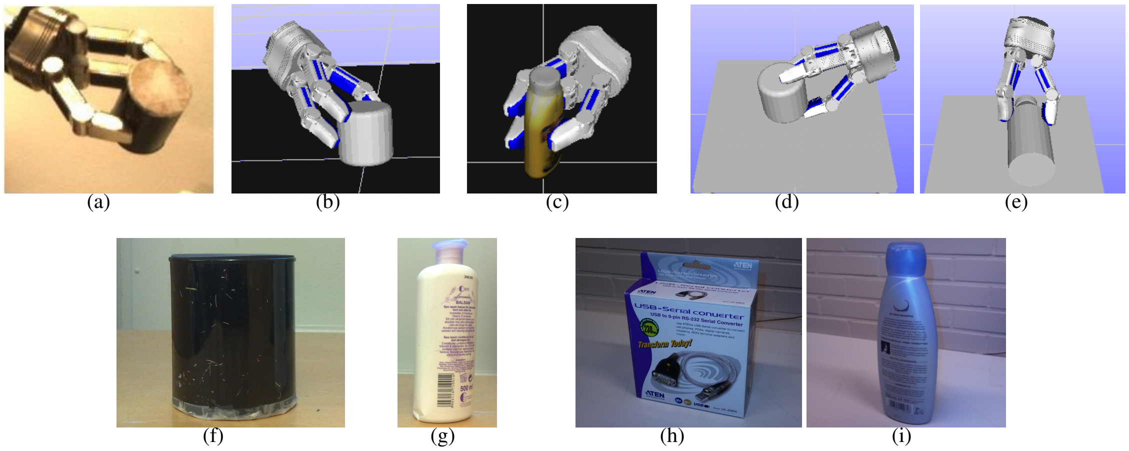

Fig. 1. Hardware and objects used in the datasets: (a) 3-finger SDH; (b) D_1; (c) D_2,D_3; (d) D_4; (e) D_5; (f) D_6; (g) D_7,D_8; (h) D_9; (i) D_{10}, D_{11}.

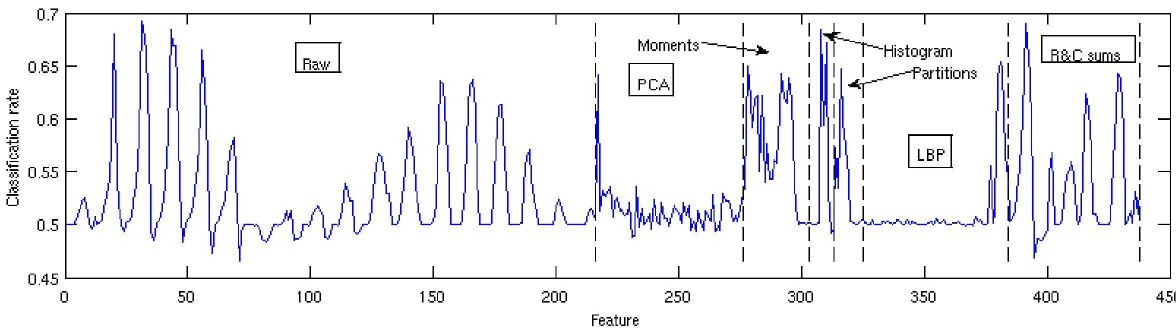

Fig. 2. Classification rates on individual features.

each dimension of all the feature representations described in Section III and also on the raw tactile data. The classification rates are shown in Figure 2 for the dataset D_1.

Classification rates of 0.5 or less in Figure 2 are a sign that the feature used is not particularily useful in learning as it has no correlation with the grasp stability. The figure shows that there are quite many useful features in the set of features that were tested. What is interesting is the raw data as it has multiple spikes which are among the best features for classifying the grasp stability. This indicates that individual cells of the tactile sensors can be used to determine the grasp stability to some extent. Also image moments, histogram and row and column sums seem to have a number of good features to use for classifying. The experiment was also performed on the real data set D_6, for which the results were similar.

VI. Conclusions and Future Work

The focus of the presented work was to investigate how different machine learning methods and feature representations affect the ability to learn and assess the grasp stability from haptic data. Both simulated and real world data was used in an experimental comparison. Experiments indicated that AdaBoost was the best performing classifier, suggesting that boosting approaches would be likely candidates for further studies in the context of grasp stability learning.

The classification performance varied significantly between different data sets. Results of the experiments showed that deformable objects are more difficult to learn with a similar sample size compared to rigid objects. A temporal approach might be useful for deformable objects, as it could extract more information from the grasp, as in [9]. Data also show that if the grasped object has contacts with the hand outside of the tactile matrices, the grasp stability can not be learned effectively. It needs to be noted that perfect classification performance is not necessary, since acceptance threshold can be set such that for example regrasping is triggered in ambiguous cases.

Future work will concentrate on expanding the presented study. Especially the study on deformable objects is interesting as currently there are no grasping simulators that are able to do this, but many household objects have this property. It is also possible to combine data from multiple objects to produce a common classifier for all the objects. Further research on this subject would help to identify the limits of the presented learning approach on completely unknown objects.

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TABLE IV

CLASSIFICATION RATES FOR DATASETS $D_{1,\cdots,11}$.

Data, Feature	SVM	GMM	KNN	AdaBoost
D_1	**75.5%**	-	*73.3%*	**76.7%**
D_2	**59.1%**	-	**56.6%**	**58.1%**
D_3	**60.3%**	-	**60.7%**	**62.1%**
D_4	69.7%	-	*63.1%*	**79.3%**
D_5, Raw	65.7%	-	*58.2%*	**68.9%**
D_6	**82.6%**	-	**90.7%**	**91.4%**
D_7	*22.0%*	-	**84.0%**	**91.0%**
D_8	*49.3%*	-	**84.6%**	**80.4%**
D_9	*54.0%*	-	**71.3%**	**71.1%**
D_{10}	**49.3%**	-	**48.6%**	**46.4%**
D_{11}	**50.0%**	-	**54.0%**	**56.0%**
Mean	66.3%	-	*62.6%*	**69.6%**
D_1	**77.0%**	74.1%	*72.5%*	74.5%
D_2	**59.7%**	56.5%	*56.1%*	57.0%
D_3	**61.3%**	**60.4%**	**59.7%**	**60.4%**
D_4	74.0%	68.7%	*67.5%*	**77.6%**
D_5, PCA	**67.6%**	64.5%	*60.4%*	**67.7%**
D_6	**85.7%**	-	*58.6%*	**90.0%**
D_7	**77.0%**	-	*55.0%*	**69.0%**
D_8	50.0%	-	*47.9%*	**78.6%**
D_9	**73.2%**	-	**65.5%**	**71.7%**
D_{10}	**50.0%**	-	**54.0%**	**54.0%**
D_{11}	**46.0%**	-	**55.0%**	**49.0%**
Mean	**68.5%**	65.4%	*63.3%*	**68.1%**
D_1	**76.5%**	*71.1%*	72.5%	**75.9%**
D_2	**61.1%**	*52.7%*	57.4%	**58.6%**
D_3	**62.7%**	*54.0%*	**60.1%**	**62.3%**
D_4	**80.0%**	*61.2%*	72.3%	**79.7%**
D_5, Moments	**70.5%**	*51.8%*	63.6%	**68.9%**
D_6	**92.1%**	-	**93.6%**	**90.7%**
D_7	**91.0%**	-	**86.0%**	**92.0%**
D_8	*27.1%*	-	**67.1%**	**77.9%**
D_9	**64.6%**	-	**69.5%**	**72.7%**
D_{10}	**44.0%**	-	**50.5%**	**44.7%**
D_{11}	**48.0%**	-	**51.0%**	**64.0%**
Mean	**70.6%**	*58.0%*	65.6%	**69.7%**
D_1	**73.1%**	*64.9%*	65.6%	**73.9%**
D_2	**56.0%**	**55.0%**	*52.2%*	**56.4%**
D_3	**62.0%**	*49.9%*	57.6%	**62.1%**
D_4	**79.0%**	71.9%	*69.8%*	**79.4%**
D_5, Histogram	**67.9%**	**66.8%**	*62.1%*	**68.5%**
D_6	**90.0%**	-	**81.4%**	**90.0%**
D_7	**84.0%**	-	**76.0%**	**82.0%**
D_8	**66.1%**	-	**73.6%**	**72.5%**
D_9	**63.0%**	-	**53.8%**	**57.3%**
D_{10}	**57.6%**	-	**49.2%**	**59.0%**
D_{11}	*38.0%*	-	**62.0%**	**57.0%**
Mean	**68.1%**	62.9%	*62.0%*	**68.7%**

TABLE V

CLASSIFICATION RATES FOR DATASETS $D_{1,\cdots,11}$.

Data, Feature	SVM	GMM	KNN	AdaBoost
D_1	**76.1%**	*65.6%*	71.8%	**75.8%**
D_2	**57.3%**	**55.0%**	**56.2%**	**57.3%**
D_3	**62.6%**	*53.2%*	59.0%	**60.8%**
D_4	**80.4%**	*65.7%*	73.0%	**79.7%**
D_5,Partitions	**69.0%**	*60.9%*	64.7%	**68.9%**
D_6	**91.3%**	-	**91.4%**	**92.1%**
D_7	**91.0%**	-	**89.0%**	**89.0%**
D_8	*36.8%*	-	**81.8%**	**67.5%**
D_9	**63.0%**	-	**60.6%**	**64.4%**
D_{10}	**40.8%**	-	**45.5%**	**48.8%**
D_{11}	**56.0%**	-	**48.0%**	**64.0%**
Mean	**69.6%**	*60.6%*	65.5%	**69.2%**
D_1	**75.0%**	*64.4%*	68.6%	**74.9%**
D_2	**54.8%**	52.0%	*51.4%*	**56.4%**
D_3	**60.9%**	*58.0%*	58.1%	**61.3%**
D_4	75.2%	66.4%	*64.0%*	**79.7%**
D_5, LBP	66.4%	58.7%	*57.8%*	**68.4%**
D_6	**84.3%**	-	**79.3%**	**85.0%**
D_7	*26.0%*	-	**68.0%**	**74.0%**
D_8	**47.1%**	-	**68.2%**	**60.0%**
D_9	**61.1%**	-	**69.2%**	**73.4%**
D_{10}	**50.2%**	-	**45.8%**	**48.3%**
D_{11}	**50.0%**	-	**49.0%**	**51.0%**
Mean	66.8%	*60.1%*	60.3%	**68.7%**
D_1	**76.8%**	*63.8%*	72.1%	**76.5%**
D_2	**61.4%**	58.6%	*57.8%*	58.3%
D_3	**62.7%**	**61.5%**	**61.5%**	**60.7%**
D_4	77.3%	*58.9%*	70.2%	**79.6%**
D_5, R&C Sums	**68.7%**	63.4%	*62.6%*	**68.8%**
D_6	**92.1%**	-	**92.1%**	**91.4%**
D_7	**90.0%**	-	**87.0%**	**91.0%**
D_8	*30.7%*	-	**72.1%**	**68.2%**
D_9	**63.5%**	-	**67.5%**	**74.6%**
D_{10}	**55.1%**	-	**50.3%**	**43.8%**
D_{11}	**54.0%**	-	**52.0%**	**64.0%**
Mean	**69.8%**	*61.6%*	65.1%	**69.5%**

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