IMPROVING TELEOPERATION PERFORMANCE USING SPATIAL ABILITY

Internship project report

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Abstract

In this work, we described the various tests through which we can measure cognitive spatial ability of a participant. Using these spatial ability scores and the performance of participants during the teleoperation tasks, We predicted the expected number of collisions and total number of objects dropped during the teleoperation task. We finally described about the assessment of a participant's teleoperation performance.

Keywords: Teleoperation, Spatial ability, Peg-in-hole, Machine Learning, Deep Learning.

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Chapter 1

Introduction

1.1 Motivation

There has been a lot of research in the field of teleoperation. Teleoperation helps in the execution of various tasks which are not feasible for humans due to dangerous working conditions. Using teleoperation, a human operator can remotely give instructions to a robot and accomplish a task without coming in harm's way. Teleoperation requires a complex combination of the operator's cognitive, perceptual, and motor skills. Many experiments show that the spatial ability of an operator is significantly correlated with the ability to teleoperate. Therefore, a teleoperator needs to have a minimum level of spatial cognitive ability to perform a task successfully. Spatial cognitive ability scores can be used to increase precision of a teleoperation task and also find out if a person is fit for it.

1.2 Aim

1. **Assess the fitness level of a teleoperator** - There exists a relation between spatial ability and the ability to teleoperate, We can identify a list of computer implementable and repeatable test that can be used to assess spatial ability. . These test scores can be used to measure if the person is fit for the role

2. **Increase the precision of the teleoperation task** - We can find the relation between spatial ability and other parameters pertaining to a teleoperation task. This equation can be used to improve the precision of the movements which will help in preventing any accidents and improve the efficiency of teleoperation task.

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Chapter 2

Theoretical Aspects

2.1 What is Cognitive Spatial ability?

Spatial ability is the capacity to understand and remember the spatial relations among objects. This ability can be viewed as a unique type of intelligence distinguishable from other forms of intelligence, such as verbal ability, reasoning ability, and memory skills.

2.2 How is it important to us ?

Good spatial awareness allows us to understand the environment and our relationship to it. Spatial perception also consists of understanding the relationship between two objects when there is a change in their position in space. It helps us think in two and three dimensions, which allows us to visualize objects from different angles and recognize them no matter the perspective that we see them from.

2.3 Types of Spatial abilities

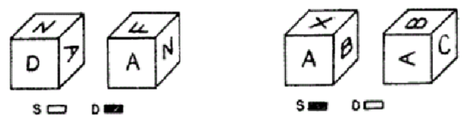
We can do Nadi Pariksha by placing our three fingers 2 cm upwards to the wrist with an index finger placed near the thumb on the radial artery as shown in Figure **??**: -

1. **Spatial Perception** - Spatial perception is defined as the ability to perceive spatial relationships in respect to the orientation of one's body despite distracting information.
2. **Mental rotation** - Mental rotation is the ability to mentally represent and rotate 2D and 3D objects in space quickly and accurately, while the object's features remain unchanged.
3. **Spatial Visualization** - Spatial visualization involves imagining and working with visual details of measurement, shapes, motion, features and properties through mental imagery and using these spatial relations to derive an understanding of a problem.

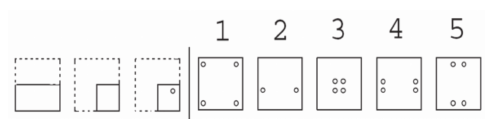
2.4 How to measure Spatial ability?

The following tests can be employed to measure the spatial cognitive ability of a person

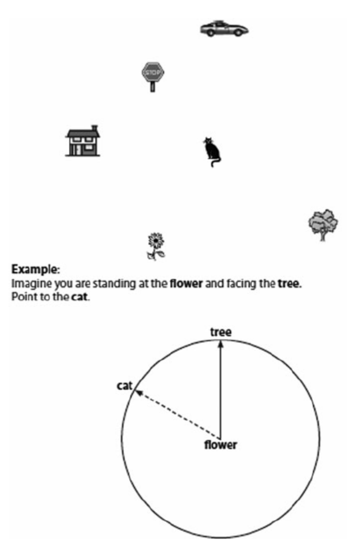
1. **Cube Comparison Test** [1] - Based on the limited images presented, the participant must decide whether the two cubes are the same or different.



2. **Paper Folding Test** [2] -This measure consists of two 10 item pages. Each item presents an image of a piece of paper, and two to four additional images demonstrating a sequence of the piece of paper being folded. On the final folded image, a 38 circle indicates a hole punched through the paper. The object of the task is to select one of five correct image representations of the unfolded piece of hole-punched paper.

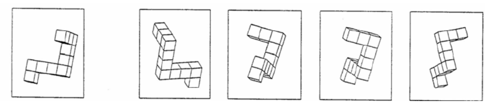


3. **Hegarty's Perspective-taking Test** [5] - This is a test of ability to imagine different perspectives or orientations in space. On each of the questions, there is a picture of an array of objects and an "arrow circle" with a question about the direction between some of the objects. The task is to draw an arrow from the center object showing the direction to a third object from this facing orientation.

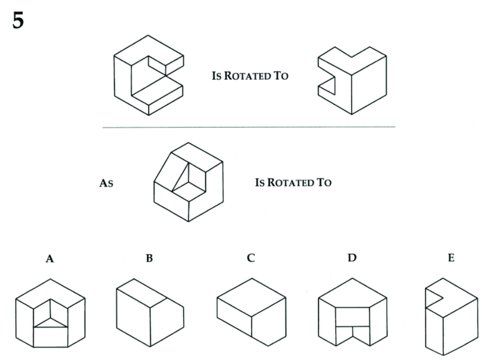


4. **Vandenberg mental rotation test** [7] -Here each target stimulus is presented along with four other options. All the four options are similar looking three-dimensional tube

like figures with three arms. However, only two among these images are that of the target stimulus, although rotated into different orientations. The subject has to identify both the correct images in order to get a score. There are 24 items and the time allotted is 6 minutes.



5. **Purdue Visualization Test [3]** -The Purdue Visualization Test is an instrument to measure spatial visualization ability in 3-D mental rotation of individuals aged 13 and over. The psychometric instrument has 2 practice items followed by 30 test items that consist of 13 symmetrical and 17 asymmetrical figures of 3-D objects, which are drawn in a 2-D isometric format



As most of these tests have Multiple Choice Questions, both paper and computer based versions of these tests exist.

Chapter 3

Literature Review

Multiple studies have been conducted that try to find a relation between spatial ability and teleoperation performance. Usually this is done by employing a set of spatial ability tests followed by a set of robot tests and then try to find a relation between the two.

Joshua Gomer conducted an experiment with 120 participants where each participant first completed eight cognitive ability tests followed by two types of robot tests under direct line of sight and teleoperation. [4] He found that there was a correlation between aggregate spatial ability scores and the aggregate robot test scores. He found that the paper folding test and the Cube Comparison test were the best predictors of teleoperation performance. He also found that males in general had much better aggregate spatial ability and robot test scores than females and also found a strong correlation between gaming experience and teleoperation performance.

Inference- Using the results of the experiments done by Joshua, we can also use tests like cube comparison test and paper folding test for measuring the cognitive spatial ability of a participant.

Alejandra Mechaca and Andrew M. Liu studied the correspondence between space teleoperation and Spatial ability scores [6]. They employed the Cube Comparison Test, Perspective Taking Ability Test and Purdue Spatial Visualization of Views Test. To measure the teleoperation performance, a simulation was created where each subjects had to manipulate an arm to capture the module and then dock it onto the node. The angular and positional offsets were measures of success for the simulation. They were hence able to find relations between spatial ability scores and teleoperation performance in terms of time taken and the positional and angular offsets. Gap analysis- The experiment was conducted on a very small population. Testing on a large population will give more accurate results.

Further, [8] discusses the role teleoperation could play a role in decommissioning of nuclear plants. They conducted experiments to find how well humans are able to control robots remotely and the challenges that they might face. They conducted an experiment with 16 participants where they conducted a spatial ability test involving two questions that assessed 2D rotation, two assembly and four 3D rotation/folding. A final question consisted of matching 2D rotations between two groups of 25 images. They then conducted a teleoperation test as well and found correspondence between spatial ability scores and teleoperation performance. We use their data set as the initial data set for our experiment. Gap analysis- The number of participants involved in the experiments were only 16. Inference- This paper predicted the value spatial ability using the error during teleoperation performance. A larger synthetic data can be generated from this Data set which can be used for getting the error from the given value of spatial ability. This can be further used for the correction of teleoperation task.

Chapter 4

Methodology

4.1 Project Workflow

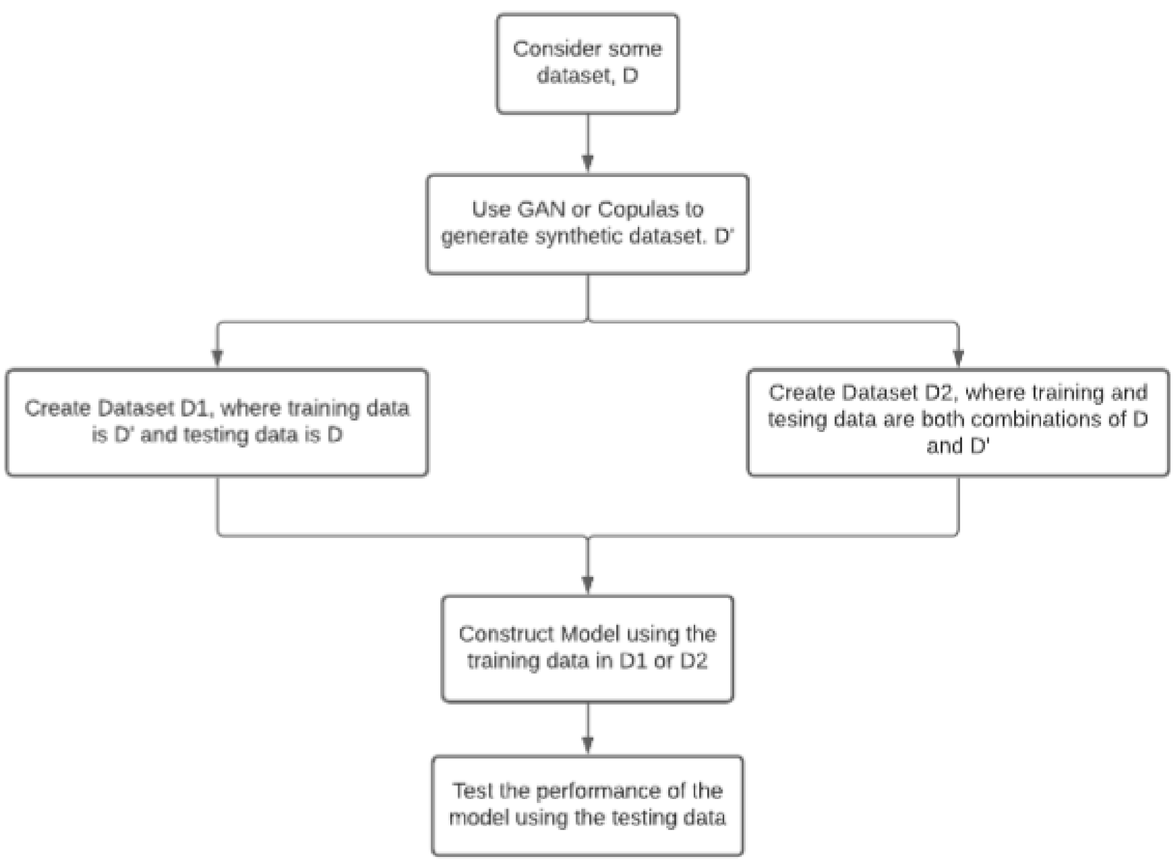


Figure 4.1: Project Workflow

4.2 Dataset Generation

4.2.1 Initial Dataset

The following dataset is used as a base for synthetic data generation [8]

1. **Teleoperation Task** - Each participant was tasked with grasping and stacking five wooden cubes to assemble a tower.

2. **Spatial Ability Test** - Two questions assessed 2D rotation, two assembly and four 3D rotation/folding. A final question consisted of matching 2D rotations between two groups of 25 images. Scores were scaled to 100.

COLLECTED DATA FROM BLOCK STACKING TASK, $\bar{x} = 289, \sigma = 76$. THE FOLLOWING ABBREVIATIONS ARE USED IN THE TABLE: PARTICIPANT NO. (PN), TRIALS COMPLETED (TLC), TIME TO COMPLETION (TTC), NUMBER OF COLLISIONS (NOC), NUMBER OF DROPPED OBJECTS (NOD) AND SPATIAL AWARENESS SCORE (SAS)

PN	TLC	TTC [s]		NOC		NOD		SAS
		Avg.	σ	Avg.	σ	Avg.	σ	
1	5	233	58	2.0	1.7	0.8	0.7	68.0
2	5	190	33	0.2	0.4	0.0	0.0	70.4
4	5	286	24	0.4	0.5	0.0	0.0	58.4
6	5	445	241	4.6	2.2	3.0	1.9	52.0
7	5	281	51	1.8	1.7	0.6	0.5	65.6
8*	4	260	126	2.3	0.8	0.8	0.8	80.0
9	5	301	46	0.6	0.5	1.0	1.3	64.0
10	5	322	141	2.8	1.6	1.2	1.9	52.0
11	5	245	18	2.0	0.6	0.0	0.0	88.0
12*	3	418	139	2.3	1.7	0.7	0.5	57.0
13	5	164	28	0.6	0.8	0.2	0.4	65.0
14	5	278	85	0.6	0.5	0.0	0.0	87.0
15	5	309	15	1.2	1.0	0.8	0.7	53.0
16*	3	309	55	0.0	0.0	0.3	0.5	84.0

4.2.2 Synthetic Dataset Generation

Since the number of participants in the initial data are too low to create a viable model, we decided to generate synthetic data first. We tried two methods -

1. **ctGAN (Conditional Tabular Generative Adversarial Network)** - A GAN (Generative Adversarial Network) is a model consisting of two main components - A generator and a discriminator. The generator produces the synthesized data, while the discriminator learns to distinguish the synthetic data from the real data. These two components compete against each other to drive the whole system towards optimization.

Tabular data can present the challenges of mixed data types, different distributions in each column and imbalanced datasets. To tackle these issues CTGAN (Conditional Tabular GAN) was developed. In CTGAN, the mode-specific normalization technique is leveraged to deal with columns that contain non-Gaussian and multimodal distributions, while a conditional generator and training-by-sampling methods are used to combat class imbalance problems

2. **Copulas** - Given a table containing numerical data, we can use Copulas to learn the distribution and later on generate new synthetic rows following the same statistical properties.

   The key intuition underlying copula functions is the idea that marginal distributions can be modeled independently from the joint distribution. For example, consider a dataset with two columns containing age and income. A copula-based modeling approach would -

   (a) Model age and income independently, transforming them into uniform distributions using the probability integral transform.

   (b) Model the relationship between the transformed variables using the copula function.

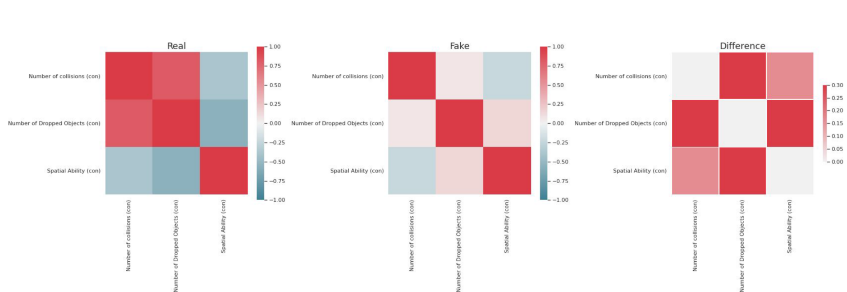


Figure 4.2: Method 1: Using ctGAN

Figure 4.3: Method 2: Using Copulas

While most parameters such as distribution, mean and standard deviation of both Copulas and ctGAN came out to be close to the real data, the correlation between features in the two methods came out to be very different. As observed from Figure 4.3, we can see that the correlations between the features is much closely simulated in case of Copulas than when compared with ctGAN. Hence, we found copulas to generate better synthetic data from our

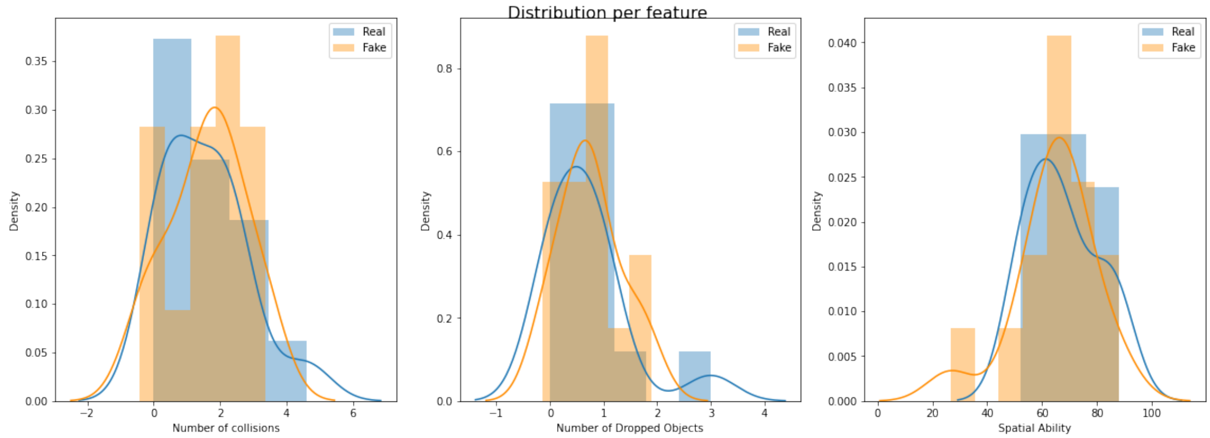


Figure 4.4: Distribution per feature for Copulas

initial dataset. The distribution mean and standard deviation for the data generated has been displayed below when compared to the real data.

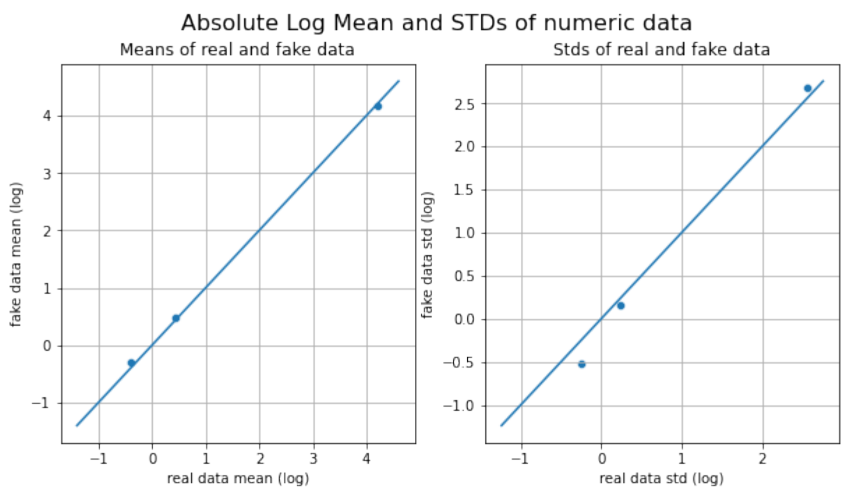


Figure 4.5: Mean and Standard Deviation for Copulas

4.2.3 Train- Test split

We create two different datasets once we have generated synthetic data. The datasets are created in the following way -

1. **Dataset 1**
   (a) Train Data - Same as synthetic dataset
   (b) Test Data - Same as the real dataset

Data	Real Data	Synthetic Data
Training set	0	1000
Testing set	14	0

2. **Dataset 2**

    (a) Train Data - We consider 80 percent of the synthesized data and 10 rows from the real dataset

    (b) Test Data - We consider the remaining 20 percent of the synthesized data and the remaining 4 rows from the original dataset

Data	Real Data	Synthetic Data
Training set	10	800
Testing set	4	200

Chapter 5

Results

5.1 Findings

We ran various machine learning model on both the datasets. The table shown below shows the deviation of the predicted spatial ability value from the original spatial ability value(Ground truth) when a model is constructed using Number of Dropped Objects and Number of Collisions as the features and Spatial Ability is used as the target.

Model name	<5 % deviation	<10 % deviation	<15 % deviation	<20 % deviation	<25 % deviation	<30 % deviation	<35 % deviation
Linear regression	28.57142857	42.85714286	50	85.71428571	100	100	100
SVM	14.28571429	35.71428571	57.14285714	92.85714286	100	100	100
KNN	28.57142857	57.14285714	64.28571429	85.71428571	92.85714286	100	100
Random Forest	14.28571429	28.57142857	64.28571429	78.57142857	85.71428571	92.85714286	100
MLP	14.28571429	35.71428571	71.42857143	85.71428571	92.85714286	100	100

Figure 5.1: Dataset 1

Model name	<5% deviation	<10% deviation	<15 % deviation	<20 % deviation	<25 % deviation	<30 % deviation	<35 % deviation
Linear regression	24.36386768	48.7913486	66.79389313	80.08905852	88.29516539	92.55725191	94.78371501
SVM	25	50.38167939	69.27480916	83.01526718	89.63104326	93.32061069	95.54707379
KNN	20.22900763	42.17557252	58.4605598	71.69211196	81.55216285	88.48600509	92.55725191
Random Forest	24.55470738	46.94656489	64.69465649	77.98982188	87.53180662	91.98473282	94.40203562
MLP	25	50.69974555	69.33842239	83.33333333	89.88549618	93.57506361	95.54707379

Figure 5.2: Dataset 2

The above table displays the deviation of the predicted spatial ability from the ground truth. Each cell displays the percentage of data within the deviation threshold defined in that column. Hence, we can conclude that if we want to predict spatial ability from number of dropped objects and number of collisions, then SVM performs well and can predict 92 percent of the data with less than 20 percent deviation.

We then constructed separate models for predicting Number of Collisions from Spatial Ability and Number of Dropped Objects from Spatial Ability. To test the performance of these models, we feed the predicted values back into the model defined above and compare the input Spatial Ability and the predicted spatial ability.

Model name	<5% deviation	<10% deviation	<15 % deviation	<20 % deviation	<25 % deviation	<30 % deviation	<35 % deviation
Linear regression	28.57142857	42.85714286	57.14285714	92.85714286	100	100	100
SVM	28.57142857	35.71428571	42.85714286	57.14285714	78.57142857	100	100
KNN	21.42857143	21.42857143	35.71428571	42.85714286	85.71428571	100	100
Random Forest	21.42857143	35.71428571	42.85714286	64.28571429	78.57142857	85.71428571	100
MLP	28.57142857	35.71428571	42.85714286	57.14285714	78.57142857	100	100

Figure 5.3: Dataset 1

Model name	<5% deviation	<10% deviation	<15 % deviation	<20 % deviation	<25 % deviation	<30 % deviation	<35 % deviation
Linear regression	31.25	55.55555556	74.74747475	85.60606061	90.97222222	93.68686869	95.45454545
SVM	24.87373737	45.39141414	62.94191919	76.07323232	83.96464646	88.63636364	91.28787879
KNN	25.12626263	47.72727273	65.78282828	76.64141414	85.85858586	90.27777778	93.62373737
Random Forest	24.36868687	45.89646465	63.38383838	76.32575758	84.28030303	89.52020202	92.04545455
MLP	24.93686869	45.51767677	63.51010101	76.01010101	83.6489899	88.13131313	90.8459596

Figure 5.4: Dataset 2

The above table displays the deviation of the predicted spatial ability by model 1 from the input spatial ability for model 2. Each cell displays the percentage of data within the deviation threshold defined in that column. Hence, we can conclude that if we want to predict number of collisions and number of dropped objects from spatial ability, then Linear Regression performs well and can predict 90 percent of the data with less than 25 percent deviation.

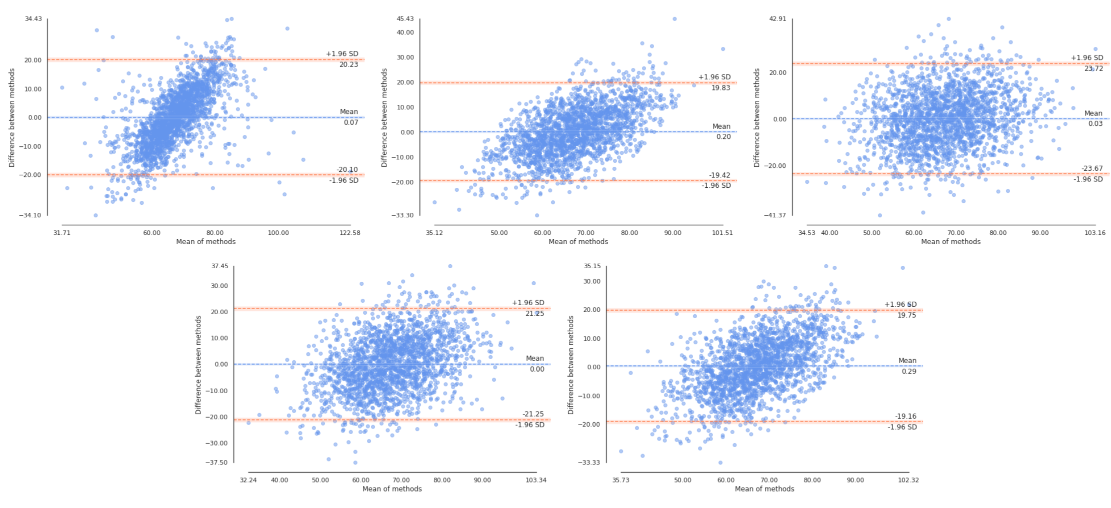


Figure 5.5: Bland Altman plots for Linear Regression, SVM, KNN, Random Forest, MLP in clockwise direction for predicting spatial ability using number of dropped objects and number of collisions

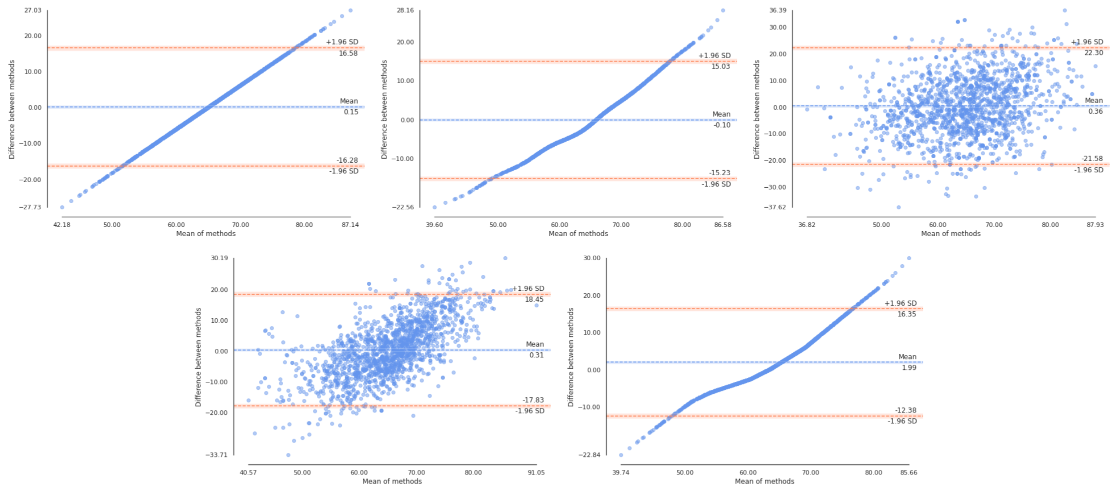


Figure 5.6: Bland Altman plots for Linear Regression, SVM, KNN, Random Forest, MLP in clockwise direction for predicting number of dropped objects and number of collisions using spatial ability

5.2 Conclusion

The above findings along with the Spatial Ability Tests explained earlier in Chapter 2 can be used to achieve our first aim, i.e. assessing the fitness level of a teleoperator. We can use the following steps to assess a teleoperator's spatial ability -

1. Employ one or a combination of multiple spatial ability tests on a potential teleoperator.
2. Get an aggregate Spatial Ability Score for the teleoperator.
3. This spatial ability score can then be passed as input into the model derived above.
4. Hence, we can get the predicted number of collisions and the predicted number of dropped objects for the teleoperation task.
5. These quantities can then be used to identify if a teleoperator is fit to perform the task.

Chapter 6

Future Work

We have currently looked into how we can predict spatial ability using total number of collisions and total number of dropped objects as features. Using the model obtained we would like to estimate number of collisions and number of dropped objects using spatial ability calculated from standardized tests discussed before. Further, we can conduct our own study where we can record the angular and positional offsets as well similar to [6]. Using such a data set, we should be able to predict the adjustments that one needs to make according to the spatial ability of the operator.

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