

# Parametric Prediction of Optical Tracker using Machine Learning Techniques for an efficient Head Tracking

Aman Kataria, Smarajit Ghosh, Vinod Karar

Abstract: A head tracker is a crucial part of the head-mounted display systems, as it tracks the head of the pilot in the plane/cockpit simulator. The operational flaws of head trackers are also dependent on different environmental conditions like different lighting conditions and stray light interference. In this paper, an optical tracker has been employed to gather the 6-DoF data of head movements under different environmental conditions. Also, the effect of different environmental conditions and variation in distance between the receiver and optical transmitter on the 6-DoF data is analyzed. This can help in the prediction of the accuracy of a optical head tracker under different environmental conditions prior to its deployment in the aircraft.

Keywords: Machine Learning, Head Tracking, Random Forest, Optical Head Tracking, Aviation

## I. INTRODUCTION

Head tracking has always been a significant part in designing of Head-mounted display systems (HMDs). HMDs are considered an integral part of fighter aircraft avionics. A head tracker is a crucial part of the HMDs, as it tracks the head of the pilot in the plane/cockpit simulator to synchronize the view of the outer world with the view in the HMDs. There are various types of head trackers which work with different tracking techniques. Their operational flaws are also dependent on different environmental conditions which are different lighting conditions and stray light interference.

Tracking can be positional or orientation in terms of coordinates and when both are combined, the system is recognized as six degrees of freedom (6-DoF) system [1]. Directions of head tracking in a 6 DOF system are X, Y, and Z which are known as positional coordinates and Roll, Yaw and Pitch known as orientation coordinates. TrackIR<sup>TM</sup> 5 Optical head tracker is used to track the six DOF directions of head

Manuscript published on 30 September 2019

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movement. To generate the Infrared (IR) light as a source TrackIR<sup>TM</sup> 5 optical tracker is used. The IR light generated by TrackIR<sup>TM</sup> 5 optical tracker acts as incoming IR light and is reflected back by the three retro-reflective markers. The three retro-reflective markers are combined is known as TrackClip which is usually placed on the helmet/head of the pilot. The infrared camera present in TrackIR<sup>TM</sup> 5 detects the the IR light reflected by the TrackClip. Finally, the orientation and positional coordinates of the head of the pilot are tracked. Experiments were conducted under different light intensities (LI) and different distance range values between transmitter and receiver (tracker) on which the performance of an optical strongly depends. Generally, the expected performance of an optical tracker diverges largely if the stray light interference is more. Each optical tracker has limited work capacity under some particular LI [2]. In the experiment, the 6-DoF data is predicted through different machine learning methods under different light intensity and distance variation between sensor and transmitter to virtually judge the performance of an optical tracker [3]. A desirable predictive method is required which can predict the 6-DoF data under a different light intensity of the environment and distance between transmitter and receiver [4]. According to the variations in environmental conditions, an appropriate number of trackers could be incorporated in a HMDs. Also in

Machine learning has been used to a great extent in predicting mathematical and statistical optimization [5]. In the proposed work, four methods of machine learning applied to predict the 6-DoF data under different light intensities and the distance between the transmitter (infrared light source) and receiver (optical receiver). Six DOF directions of head tracking are analyzed for different environmental conditions. For predicting the output, Random forest, Neural networks, Generalized linear model (GLM) and Support vector machine (SVM) is used. K-fold cross validation is used to prove the robustness and stability of the best prediction method [6].

the aircraft simulator, it can help to choose the appropriate

optical tracker according to the environmental condition of

The remaining paper is structured with Section II presents the experimental setup, Section III represents the methodology used. Section IV represents the methods of machine learning. Model evaluation is described in section V. Results are discussed in section VI. Finally, conclusion

and future scope is presented in section VII and section VIII respectively.

simulator bed.



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#### II. EXPERIMENTAL SETUP

For carrying out desired experimentation conditions, the Cockpit Simulator is used. It comprised of a pilot seat at a designated distance from the transmitter. The aircraft canopy covered the head-up display along with the optical transmitter. The receiver (infrared retro-reflector) was mounted on the user cap. The diffused light source controlled the ambient light variations, while the pilot movement simulated the distances between the transmitter and the receiver. TrackIR 5<sup>TM</sup> is used to track the head movements in Display Simulator. To measure the light intensity Lux Meter ("Model TES 133x DLM") is used.

# a) Display Simulator



Fig.1. Display Simulator with optical tracker TrackIR 5<sup>™</sup> (Shown in red circle) at CSIR- CSIO

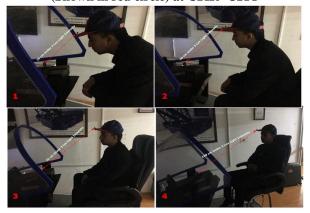


Fig.2. The experiment conducted under 3 lux light intensity with different distances 25cm, 50cm, 75cm and 100cm represented by numeric 1-4 respectively.



Fig.3. The experiment conducted under 75 lux light intensity with different distances 25cm, 50cm, 75cm and 100cm represented by numeric 1-4 respectively.



Fig.4. The experiment conducted under 111 lux light intensity with different distances 25cm, 50cm, 75cm and 100cm represented by numeric 1-4 respectively.

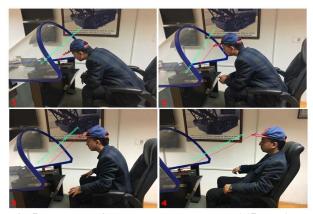


Fig.5. The experiment conducted under 165 lux light intensity with different distances 25cm, 50cm, 75cm and 100cm represented by numeric 1-4 respectively.



Fig.6 Lux meter readings under different light intensity.

#### III. METHODOLOGY

# a) Description of Data Set and its Features

Data set have been modeled after performing experiments under different conditions viz. variation in light intensity and variation in distances between the transmitter and the receiver. Description regarding movements of the head in optical head tracking used in the experiment has been described in Table I.



Table- I: Description of the movements of head recorded by an Optical Tracker

DoF	Information
X	Forward and backward translational coordinate of the
	pilot's head
Y	Left and right translational coordinate of the pilot's
	head
$\mathbf{Z}$	Up and Down translational coordinate of the pilot's
	head
Yaw	Rotational coordinate of the pilot's head along Z-axis
Pitch	Rotational coordinate of the pilot's head along Y-axis
Roll	Rotational coordinate of the pilot's head along X-axis

## b) Quantitative Assessment

Experiments conducted with light intensity and distance variation between the transmitter and the receiver helps in the prediction of the desirable conditions in which optical tracker give satisfactory output. Light intensity is measured as the rate at which energy of light is delivered per unit surface per unit time per unit area. Light intensity is measured in Lux (lx). The experiments are conducted for light intensity varying from 4 lux to 166 lux. In the experimentation, the distance between the pilot's head (transmitter is located on the cap worn on head) and the receiver are kept in four distances: 25cm, 50cm, 75cm and 100cm. Values of light intensity, distances between transmitter and receiver and sample values of 6-DOF head tracking coordinates are provided in Table-II.

Table-II: Sample set of Data

Table-11; Sample set of Data							
Light	Distan	Yaw	Pitch	Roll	X	Y	$\mathbf{Z}$
intensit	ce (in						
y (in	cm)						
lux)							
3	25	-18.2	3.8	-17	-4.5	4.1	13.47
3	50	-20.5	-1.7	-7.8	0.2	0.7	-10.3
3	75	-23.5	-12.7	-2.6	-13	-0.2	3.97
3	100	5.1	-14.4	-2.9	6	0.7	-5.13
75	25	-54.3	1.1	-0.6	-2.8	0.5	6.05
75	50	-49	-1.4	-1.8	-1.2	1.4	2.95
75	75	-8.8	2	-4.5	-1.9	1.3	-0.16
75	100	-11.6	1	-3.8	0.3	-1.9	-12.3
111	25	-13.1	-2.8	0.1	-7.6	3.2	5.66
111	50	-7.4	-3	0	-6.2	3.3	5.38
111	75	-2	-2.8	-0.4	-1.1	3	6.46
111	25	-16	-2.8	-0.4	2	2.9	-2.15
165	50	9.3	-6.6	2.4	0.6	2.5	-9.43
165	25	9.7	-6.1	2	1	2	-11.2
165	75	9.43	-6.67	2.4	0.6	2.5	-9.43
165	100	-10.2	-7.99	-1.8	5	2	-7.76

#### c) Feature Description

Six physical DOF directions are extensively used in the experimentation and subsequent analysis. The X coordinate, in this case, is the translation of the body along X-axis also known as forward and backward translation. Forward translation leads to a positive value and backward translation leads to negative values. The Y coordinate is the translation of the body along Y-axis also known as the left and right translation. Right translation leads to a positive value and left translation leads to negative values. The Z coordinate is the coordinate of translation of the body along Z-axis also known as up and down translation. Up translation leads to a positive value and down translation leads to a negative value. The

rotational coordinates are Yaw, Pitch, and Roll. Yaw is the rotation along Z-axis and is measured in degrees. Roll is the rotation along X-axis and is measured in degrees and Pitch is the rotation along Y-axis and is measured in degrees. The rotational matrixes of the rotational coordinates are given below:



Fig.7 Prototype view of Optical Head tracker [7]

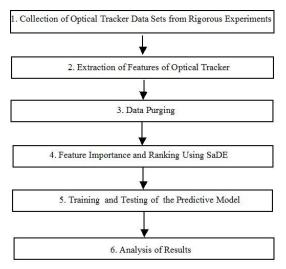


Fig.8 Methodology used

# d) Approach

The experimental approach is presented in Fig. 1-6. Data sets are collected by conducting experiments under different conditions: combinations of four distance ranges – 25 cm, 50 cm, 75 cm & 100 cm, and four light intensities - 4 lux, 75 lux, 110 lux, and 166 lux. Next, elimination of duplicate and missing entries from data set is processed as elimination of the repetitive value assures the uniqueness in experimental data set using IBM SPSS/Microsoft Excel. To describe the importance of each feature in terms of ranking, Self-adaptive differential evolution technique is used which is discussed in the next section. Next, four machine learning techniques, as shown in Table III, are learned and trained, then it is processed for testing it on a corresponding optical tracker data-set with default and predefined parameters of machine learning techniques discussed in further sections.



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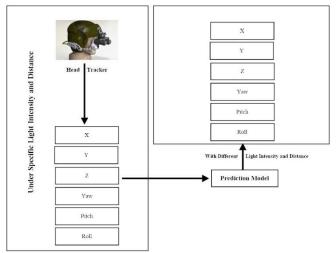


Fig.9 Prediction Model

The prediction model is described in Fig. 9. In the final stage, the evaluation of the method is done on Accuracy using (2), (3) and, (4). Robustness of the best predictive machine learning method is determined using K-fold cross-validation.

# e) Self Adaptive Differential Evolution (SaDE)

SaDE as proposed by Qin et.al [8], is one of the efficient, fast and robust algorithm to solve many types of real optimization problems. In this technique, the controlling parameter G and CO, and the choice of learning strategy is not required to be predefined. Learning strategies along with parameters, which are associated with SaDE, can be adapted automatically during the procedure of evolving. Accordingly, with SaDE, more schemes of generation with the settings of parameter is possible to find in an adaptive manner. This can help to cope up with different phases of the search evolution [9].

# Importance of Feature using SaDE

According to the objective function defined in (1) for light intensity and Distance (D), an optimized weight is assigned to all the features of the optical tracker used in this experiment. The mutation rate (MR) and crossover rate (CR) used in this algorithm are set to be 0.01 and 0.9 respectively.

Objective function=
$$min\left(\sum_{m=1}^{R}\sqrt{\left(T_{i}-\sum_{s=1}^{p}w_{s}.P_{m,s}\right)^{2}}\right)$$
 (1)

where R is the total number of instances in the training data set, T will be LI and D target, P is physical parameters (X, Y, Z, Pitch, Roll, and Yaw), p is the number of features or properties (6 in this case) and w is the weight assigned to every parameter defined in the domain [0,1]. After five different instances, the description of the average weight assigned to each feature as also shown in Table IV for LI and D range. The average weight obtained is used to rank the features. According to SaDE algorithm, it is found that Pitch has the highest-ranking and Roll has the lowest ranking. Ranking based on perturbations caused in 6-DoF data due to different light intensities and distance between transmitter and receiver may help in selecting the appropriate optical tracker or other tracking technology trackers like a magnetic or inertial head tracker.

Table III Machine Learning Packages used in open-source software R

Model	Package	Parameter Reference setting	
R Forest	mtry	Number of tree = 500	[14]
LM	stats	head-mounted	[11]
SVM	e1071	Epsilon = $0.5$ ; $nu = 10$	[12]
NN	neuralnet	MaxNWTs = 10000; hlayers = 10; maxit = 100	[13]

Table-IV Perturbation ranking of the 6-DoF data of TrackIR Optical tracker using SADE

	6 –DoF Movements					
	Pitch	Y	X	Z	Yaw	Roll
Different				,		
Distance	79.7	74.4	60.1	75.1	5.9	49.6
Different	! 					
Light	83.3	80.0	62.5	82.2	70.2	47.6
Intensity	00.0	00.0	02.0	02.2		.,.0
Average	81.5	77.2	61.3	78.7	68.1	48.6
Perturbat						
i-on	1	2	5	3	4	6
Ranking						

# IV. METHODS OF MACHINE LEARNING

In this experiment, four different machine learning techniques as shown in Table III, are used for predicting 6-DoF data under different LI and Distance range between pilot's head (transmitter) and optical tracker (receiver). For prediction, machine learning methods used in this experiment are available on open-source software known as R licensed under GNU GPL. Methods of machine learning used are briefly discussed below:

- 1. Random Forest (randomForest): Random forest is a learning method used for classification based on the technique forest of trees utilizing the random inputs [10]. They can map nonlinear relationships, unlike the linear model. It is also known as the nonparametric method, which needs no assumptions about the distribution of data.
- 2. Linear Models (GLM): Linear models allow for response variables, which have models for error distribution other than the normal distribution. For analysis of covariance, this method uses linear models. This method also carries out a single stratum analysis of variance and regression [12]. This model lays emphasis on linear data, so if the data is linear in nature it will yield high accuracy.
- 3. Support Vector Machine (SVM): SVMs are supervised learning models with learning algorithms, which analyze data for classification analysis. SVMs are effective and robust techniques for nonlinear classification and regression [13]. SVM is used to compare the results with the other machine learning methods; however, it is a less efficient method for training purposes.
- 4. Neural Network (NN): Neural Networks are Von Neumann machines, which are based on the abstraction of information processing.



Using the backpropagation algorithm with or without weight, training of neural networks is done [14]-[16] .

NN are used because of their ability to detect the complex nonlinear relationships between the dependent and independent variables within the data set, but it yields less accuracy in this experiment due to slow computational time and proneness to over-fitting.

#### V. MODEL EVALUATION

Performance of the prediction can be measured in various ways, where one way can be more desirable than other ways which depend on the application evaluated. In this paper, by applying the same number of input variables (i.e. features of optical head tracking) two different models for the prediction of two output variables (i.e. light intensity and distance between transmitter and tracker) has been developed. The function formulated, which can be used in all the machine learning models, is described by:

Light Intensity 
$$\sim f(X, Y, Z, Roll, Yaw, Pitch)$$
 (2)

Distance 
$$\sim f(X, Y, Z, Roll, Yaw, Pitch)$$
 (3)

The accuracy in this experiment is the percentage in the deviation of the predicted target from the actual target.

Accuracy = 
$$\frac{100}{z} \sum_{s=1}^{z} f_i \qquad f_i = 1 \text{ if } \{ t_i = x_i \}$$

$$0 \text{ otherwise} \qquad (4)$$

Where x is the real target, t is predicted target, and z is the total number of instances.

# VI. RESULTS

Prediction results obtained from all the four machine learning methods have been analyzed in this Section. Training, testing, and validation have been performed through different machine learning methods. In the training-testing experimental phase, the corresponding data set consists of coordinates of X, Y, Z, Roll, Pitch and Yaw under different light intensity as well as different distances between transmitter and Head Tracker (receiver). Accuracy and sensitivity of predicted 6-DoF data using different machine learning methods have been described. The corresponding data may be low in features but it is high in observation values. Generalized results have been provided in Table V.

Table-V: Comparison of performance of different methods of machine learning for prediction of 6-DOF data under different light intensity and distances between

Madal	Distance	Light Intensity
Model	Accuracy	Accuracy
R Forest	99.05	98.03
SVM	93.21	92.22
LM	71.49	70.95
NN	51.33	52.11

Training-Testing Experiment

In training-testing phase, the distribution of data are set to [50% and 50%], [60% and 40%], [70% and 30%] and [80% and 20%] respectively for all four machine learning methods (the corresponding data set used in the experiment can be

found in the package). Table VI and Table VII provide describe the comparison of performances of all the machine learning methods in which 6-DoF data is predicted under different light intensity and distance range in terms of accuracy. It is found that Random Forest has the highest accuracy of prediction of both, 6-DoF data under different light intensities and different distances between receiver and transmitter.

Table-VI: Training and testing partition for the prediction of 6-DoF data under different light intensities

	Training testing partition					
Models	50-50% 60-40% 70-30% 80-20%					
R Forest	90.56	98.78	98.03	99.25		
Linear Model	71.77	72.88	70.95	71.56		
SVM	92.34	90.32	92.22	94.40		
NN	51.12	54.43	55.11	56.31		

Table-VII: Training and testing partition for the prediction of 6-DoF data under different distances between receiver and transmitter

Distance	Training Testing Partition					
Models	50-50%	60-40%	70-30%	80-20%		
Random	98.74	99.05	99.05	97.57		
Forest						
Linear Model	72.33	70.46	71.49	72.08		
SVM	87.14	89.30	93.21	93.20		
NN	50.15	51.13	55.83	56.64		

The performance comparison of different machine learning concludes that Random forest method has better accuracy over other machine learning methods used for prediction. Table V depicts the comparative performance of all the four methods of machine learning in the prediction of 6-DoF data under different light intensity and distances in terms of accuracy.

# VII. CONCLUSION

In this letter, four different machine learning methods (random forest, linear model, support vector machines and neural network) over experimentations with the six movements of the head in an optical head tracking have been explored on cockpit display simulator. Further, the 6-DoF data is predicted using machine learning methods under different light intensity and distances between transmitter and receiver. The experiments were conducted under different atmospheric conditions like different light intensities and different distance between transmitter and receiver. This is done to predict the working of an optical tracker under various atmospheric conditions. With the prediction percentage achieved by the various machine learning methods, it may help the pilot to choose the appropriate tracker for the tracking of the head of the pilot.

#### **FUTURE SCOPE**

A similar study can be carried out for different tracking technologies so that the machine learning predictions could help in choosing the best tracking technology. The result may be a single tracking technology or the hybridization of different technologies.



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#### ACKNOWLEDGMENT

We thank the CSIR-CSIO Laboratory for the use of their equipment and the support to conduct experiments. We also thank Dr. R.K. Sinha, Director CSIR-CSIO for his support.

#### REFERENCES

- Jurriaan D Mulder, Jack Jansen, and Arjen van Rhijn. An affordable optical head tracking system for desktop vr/ar systems. In Proceedings of the workshop on Virtual environments 2003, pages 215–223. ACM, 2003.
- 2. Greg Welch, Gary Bishop, Leandra Vicci, Stephen Brumback, Kurtis Keller, and D'nardo Colucci. High-performance wide-area optical tracking: The hiball tracking system. presence: teleoperators and virtual environments, 10(1):1–21, 2001.
- Jaime G Carbonell, Ryszard S Michalski, and Tom M Mitchell. An overview of machine learning. In Machine learning, pages 3–23. Springer, 1983.
- Andrew Kiruluta, Moshe Eizenman, and Subbarayan Pasupathy. Predictive head movement tracking using a kalman filter. Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 27(2): 326–331, 1997.
- Donald Michie, David J Spiegelhalter, and Charles C Taylor. Machine learning, neural and statistical classification. 1994.
- Mark Ward, Ronald Azuma, Robert Bennett, Stefan Gottschalk, and Henry Fuchs. A demonstrated optical tracker with scalable work area for head-mounted display systems. In Proceedings of the 1992 symposium on Interactive 3D graphics, pages 43–52. ACM, 1992.
- Adil, Fatime Zehra, Erhan İlhan Konukseven, Tuna Balkan, and Ömer Faruk Adil. Optical alignment procedure utilizing neural networks combined with Shack–Hartmann wavefront sensor. Optical Engineering 56, no. 5: 051402-051402, 2017.
- A Kai Qin, Vicky Ling Huang, and Ponnuthurai N Suganthan. Differential evolution algorithm with strategy adaptation for global numerical optimization. Evolutionary Computation, IEEE Transactions on, 13(2):398–417, 2009.
- Prashant Singh Rana, Harish Sharma, Mahua Bhattacharya, and Anupam Shukla. Quality assessment of modeled protein structure using physicochemical properties. Journal of bioinformatics and computational biology, 13(02):1550005, 2015.
- 10. Leo Breiman. Random forests. Machine learning, 45(1):5–32, 2001.
- John M Chambers. Computational methods for data analysis. A Wiley Publication in Applied Statistics, New York: Wiley, 1977, 1, 1977.
- 12. S. Sathiya Keerthi and Elmer G Gilbert. Convergence of a generalized SMO algorithm for SVM classifier design. Machine Learning, 46(1-3):351–360, 2002.
- Martin Riedmiller and Heinrich Braun. A direct adaptive method for faster back-propagation learning: The RPROP algorithm. In Neural Networks, 1993., IEEE International Conference on, pages 586–591. IEEE, 1993.
- 14. Andy Liaw and Matthew Wiener. Classification and regression by random forest. R news, 2(3):18–22, 2002.
- Kataria, A., Ghosh, S., & Karar, V. (2018). Data Prediction of Optical Head Tracking using Self Healing Neural Model for Head Mounted Display
- Sharma, V., You, I., Jayakody, D. N. K., Reina, D. G., & Choo, K. K.
   R. (2019). Neural-blockchain based ultra-reliable caching for edge-enabled UAV networks. IEEE Transactions on Industrial Informatics.

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