Deep Learning based approach for Range Estimation

Samvram Sahu
Department of Avionics
IIST
Trivandrum, India
samvram.iist@gmail.com

Anurag Shukla
Department of Avionics
IIST
Trivandrum, India
aanurag97@gmail.com

V. Adithya Krishnan
Department of Avionics
IIST
Trivandrum, India
v.adi_1997@yahoo.co.in

Pradipta Roy
Directorate of EOTS
Integrated Test Range, DRDO
Chandipur, India
pradipta32@gmail.com

***Abstract*—Range analysis is one of the most sought after topics in evaluation of airborne flight vehicles. Deterministic and statistical methods have been used for estimation of the range of flight vehicles from a point on ground. The present industrial implementation involves use of redundant sensors and apparatus at two far-off sites which has always been a problem. In this paper, we find a method to estimate the range of a flight vehicle with the use of a single camera. Deep Learning based depth mapping has provided appreciable results for shorter ranges, but this method remains unexplored for longer ranges. A Convolutional Neural Networks(CNN) based approach fares equally well with the other methods of monocular depth estimation such as linear regression, support vector machine based regression, decision tree regression by treating the range estimation problem as a regression problem. A comparison has been done among various methods that have been used to approach the problem.**

***Index Terms*—CNN, Monocular Vision, Range Estimation, Regression**

I. Introduction

Flight vehicles can be considered as a boon and bane. It finds application in both the defence sector as well as civil sector. But more than designing a flight vehicle and successfully launching it, tracking of a flight vehicle has been a major challenge faced by the defence sector. Tracking provides the information relating to the functioning of the flight vehicle and its trajectory. Conventionally this has been achieved by the use of RADARs or Telemetry applications. But with the advent of Computer Vision and its implementation into modern Defence Systems, methods like Electro-Optical Tracking System (EOTS) have become more popular.

EOTS is a camera mounted on a platform which is capable of detecting a flight vehicle in its scope, adhering a lock-on and then tracking it, mostly using Infrared (IR) imaging. During the tracking phase the camera needs the object of interest to stay in sight and hence it moves its optical axis to align with the object. The control of this device is dependent on the feed from other EOTS devices, and/or RADARs which track the flight vehicle. Usually another EOTS device is used to triangulate the position and hence find the range of the flight vehicle. This is a deterministic method and hence the error introduced are mostly attributed to measurement errors. However, the high accuracy comes at the cost of an immense number of sensors/devices used for this method.

This paper however intends to overcome the above stated problem by using monocular vision for range estimation by using various regression techniques. The paper covers all the work that has been done on making a robust regression algorithm which can estimate approximately how far a flight vehicle is in a given image. It is an application specific design that adheres to the industrial requirements. The various Regression designs use techniques like Support Vector Machine (SVM), Tree Regressor and Linear Regressor. Deep learning approach is taken in the form of CNN and ANN (Artificial Neural Networks) Regressors. A brief comparison of the performance of the mentioned methods is also shown.

A brief overview of our work is presented in this paper. *Related Work* consists of the preliminary work we reviewed in order to work on this topic, *Methodology* covers the various approaches to this problem, which is *Deterministic Approach*, *Statistical Approach* and *Deep Learning based Approach*, which in turn contains *ANN* and *CNN* based methods. in *Results & Discussion*, we discuss the observations and their corresponding inferences.

II. Related Work

A lot of research and methods are being developed for the depth estimation problem due to its use in various fields like robotics, defence, Computer Vision, and many more. Log mapping method proposed by Yamaguti et al.[10] uses complex log mapping to measure the distance between the camera and the object. Two images from two different camera positions are used in this method. Ratio between the objects sizes projected on the two images that are moved on the cameras optical axis is used for the calculation. Another such intuitive method proposed by Peyman Alizadeh[1] for object distance calculation is based on an objects position on the image. This method does not depend on the objects size. This was further researched upon by changing the pitch angle of the camera. Photometric visual servoing proposed by Tamadazte et al.[11] is a new technique to overcome the problem of the object tracking process. In photometric visual servoing, the tracking process is no longer required, since the image intensity (the pure luminance signal) is sufficient to control the robots motion. Image gradient and image entropy have the same approaches as photometric visual servoing. The image gradient technique

is based on the extraction of information of an image which is located in its high frequency areas(contours). Marchand and Collewet [9] applied a method to use the square norm of the gradient obtained from all of the pixels in an image as visual features in visual servoing. Wang and Liu [8] proposed a new visual servo control technique for the robotic manipulator, whereby a back propagation neural network would make a transition from the image feature to joint angles. Yet another method was the triangulation technique (active or passive). The active triangulation method emits a signal and then measures the reflected signals, whereas the passive triangulation method uses the background illumination.

III. Methodology

A. Deterministic Approach

The method requires some additional prerequisites before being applied as the range estimation requires few values for the geometrical analysis. The height of the camera is required for calculating the range. The angle of the camera with respect to the horizontal should be known. These two parameters are very important in the calculation of the range. This maybe considered as a demerit as the height of the camera or the height of the object may not be available.

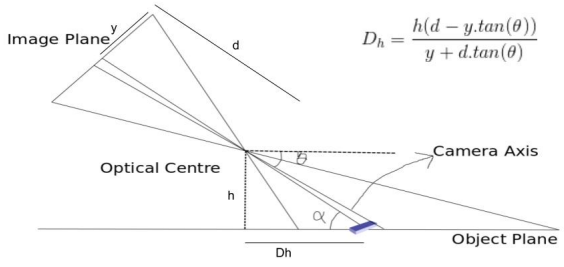

Fig. 1. Experimental setup showing the arrangement of camera and the object

The experimental setup is shown in Figure 1, Image is formed on the $Image\ plane$ where the CCD sensors reside, where y is distance of the object's image from the bottom of the sensor in the image plane, d is the focal length of the lens used in the camera, or simply the distance between the centre of the lens and the $Image\ plane$, θ is the angle of the depression of the optical axis from the local horizontal, and α is the angle of elevation from the object towards the centre of the lens. D_{Hy} is the y-direction or vertical distance from camera bottom, h is the height of the camera from ground, y is the image centroid distance from image centre in image plane, f is the focal length of the camera lens.The object is later shifted to various other positions and a dataset of ranges are calculated using the geometrical method. The ranges were checked manually also later. Theta (θ) is kept constant through out the experiment and it is assumed that the parameters f and d remain constant for all the images.

$$\begin{aligned} tan(\alpha) &= \frac{h}{D_{Hy}} \\ tan(\psi) &= \frac{y}{f} \end{aligned} \tag{1}$$

$$\begin{aligned} \theta + \psi + 90^\circ - \alpha &= 90^\circ \\ \alpha - \psi &= \theta \end{aligned} \tag{2}$$

$$tan(\theta) = \frac{tan(\alpha) - tan(\psi)}{1 + tan(\alpha) * tan(\psi)} \tag{3}$$

Solving equations $1, 2, 3$ we get -

$$D_{Hy} = \frac{h(d - y * tan(\theta))}{y + d * tan(\theta)} \tag{4}$$

Similar method can be used for distance along x-direction or the perpendicular plane. The equation comes out to be following:

$$D_{Hx} = D_{Hy} \frac{x - 0.5x}{f} \tag{5}$$

The main problem with geometric method is its inability to deal with long range objects. This can be seen mathematically in equation 6.

$$\begin{aligned} &\theta \to 0 \\ &y \times tan(\theta) \approx d \times tan(\theta) \to 0 \\ \Rightarrow\ &D_{H_y} \approx \frac{h \times d}{y} \end{aligned} \tag{6}$$

As object is placed far away from the camera, to capture the object in frame, the angle of depreciation need to be close to 0. Taking the limit θ tends to 0, we observe that the values h and d are fixed and of finite length. But y being the distance of centroid from image centre, will tend to 0 as object will lie more and more closer to the centre of the image frame. This will result in undetermined fraction form which shows that as the range increases, the error will diverge.

B. Statistical Approach

We shall estimate the range based on some prior features, thus a set of features which can perform as an input is needed. We can use the range data as an output, for devising a function or a transform.

Features used: We need to form a feature vector(F_v) from $M_{321\times321}$, and use them as inputs for regression problems. We implement a MATLAB function named **featureExtractor** which takes an image input and gives a feature vector as the output.

The output essentially consists of a vector which has 4 elements, i.e.

- Size of the object
- Average Intensity of the object
- Relative Intensity of the object
- Eccentricity of the object

Few methods which use these features for predicting the range are listed below:

1) Linear Regression: We optimize a weight vector(w), s.t. $w^T F_v \approx R$. The cost function is Root Mean Square Error which has to be minimized.We get an optimal RMSE of 10.33 % which is pretty huge and this is a unacceptable.

2) Support Vector Machine(SVM)) regression: Support Vector Machine can also be used as a regression method, maintaining all the main features that characterize the algorithm (maximal margin). RMSE for linear SVM is more or less similar to the Linear Regressor.

3) Decision Tree Regression: Decision tree method breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes. The RMSE of this regressor is the least and is in the order of 1.6 %.

C. Deep Learning Approach

CNNs are good at learning complex functions.We design an ANN based regressor which can estimate the range given an image based on the previous values.

1) Artificial Neural Network(ANN): An ANN is based on a collection of connected units called artificial neurons which loosely model the neurons in brain. We try various architectures and freeze the optimal architecture with a hidden layer. The number of neurons in the hidden layer is varied till we obtain the optimal RMSE which occurs for the case of 20 neurons.

2) CNN based Approach: We create a dataset from the previously tracked video-feed provided by the existing EOTS system. The video is split into frames, to ensure uniform distribution of training data we obtain a set of frames from a time location and randomly sample 70 percent of the frames for training, 10 percent for validation and 20 percent for test. Dataset is created from videos from different EOTS sites, hence all the co-ordinates of aerial vehicle (x,y,z) vary as per the trajectory. CNNs extract features used for regression themselves from the images. Mainly two constraints on architechture are taken from [7].

1) The ratio of real filter size of convolution to the receptive field size should not fall below $\frac{1}{6}$.
2) The receptive field size of the last neuron should not exceed the input image size.

Following configuration was used during tuning of the architecture

- Mini Batch Size - 100
- Validation Frequency - After every epoch
- Optimizer used - Stochastic Gradient Descent with Momentum
- Maximum Epochs - Experimentally determined till when network does not overfit
- Initial Learn Rate - 0.001

With an initial network we get a RMSE of around 20 kilometres which is still unacceptable, and hence we increase the depth of the architecture which can capture more complex features. The modified network fails for small value of ranges where the network predicts wrong values, this maybe attributed to the features extracted by the network, it is possible for a particular feature to fluctuate more at early ranges. We expect this network to outperform the rest. However the results suggest otherwise, this network produces the worst results thus confirming that number of layers in architecture is not a necessary criterion for regression which concurs with results in [7]. With this we take a hint that the depth should be reduced in order to deal with the problem exactly. Hence we come up with the following architecture.

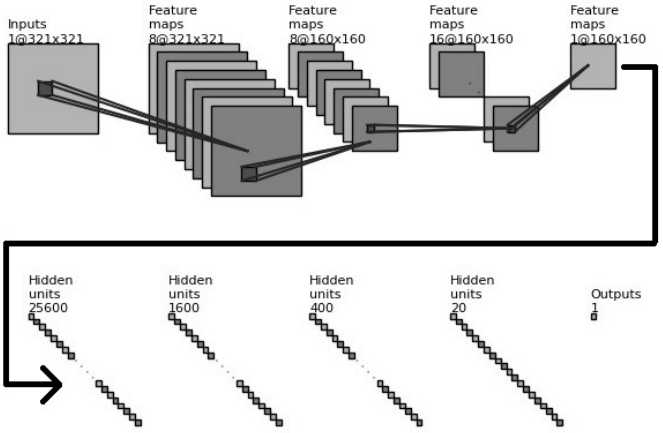

Fig. 2. Tuned Network for Application

When the network in figure 2 is trained, the best solution amongst all neural networks is obtained.

The architecture hierarchy goes as follows,

- Input Layer
- Convolution Layer - 8
- Convolution Layer - 16
- Max pooling - 1600
- Max pooling - 400
- Max pooling - 20
- Max pooling - 1
- Regression Layer

TABLE I
METHOD COMPARISON

Specification	Decision Tree	ANN	CNN
Feature Extraction	Manual	Manual	Auto
Training Time	Less	Comparable	High
Scalability	Low	High	Highly scalable
Adaptability	Low	Comparable	Highly adaptable
Data Set Required	Medium	Large	Large

*Descriptions are comparative and not to be taken absolute.

IV. RESULTS & DISCUSSION

A comparison of different methods as discussed in table II, we found some methods outperform others others in some

aspects.

The linear regressor (refer to figure 3) as expected didn't give a good results thus indicating towards the fact that the problem statement does not follow a linear behaviour.

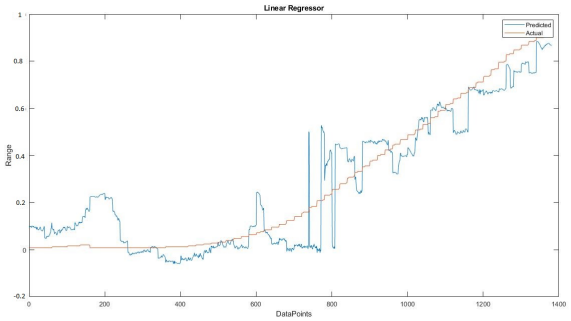

Fig. 3. The predicted range of linear regressor vaguely follows the actual range traversed, this shows non-linear dynamics in system

The use of SVM was then tried out in two parts. At first, we used a linear SVM regessor (refer to figure 4) which like the linear regressor, didn't give a good result but some improvement in the RMSE values were observed. The second part was done using a non-linear SVM regressor (refer to figure 5) which showed a little bit of improvement but still not satisfactory. This is because the root problem with SVM that it does not very well deal with scalability of features of the data set.

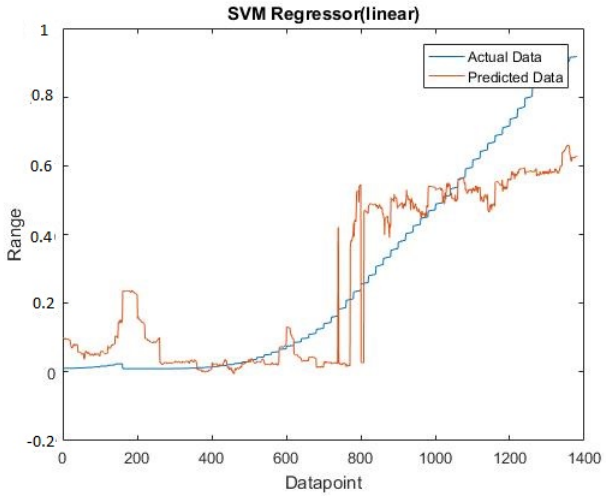

Fig. 4. SVM is a good choice for learning complex functions, using kernel tricks. Linear SVM's predicted range is better than linear regressor, but fails at higher ranges

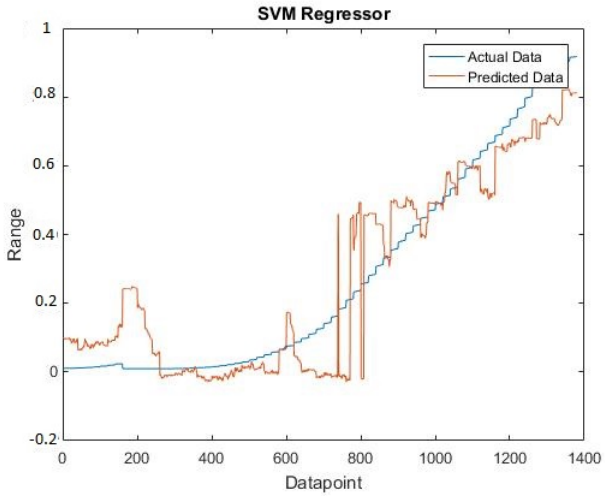

Fig. 5. Non-linear SVM performs similar to the linear SVM with improved performance at farther ranges, both fail at mid range(stage separation is bottleneck)

The decision tree regressor (refer to 6) used gave the best results among all other deterministic methods. This regressor divides the problem space into sub-regions till it can approach it for a solution hence attaining the level of accuracy. But, this is extremely sensitive to small perturbations in the data: a slight change in the data fed (from a different site) can result in a drastically different tree. Also it can easily over-fit which is an issue.

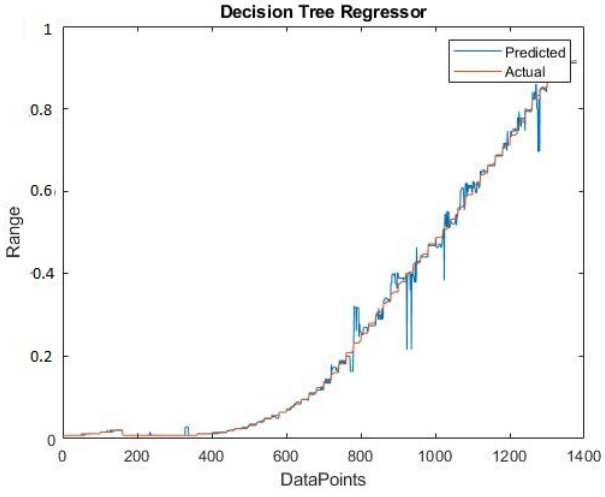

Fig. 6. Dividing the problem space into smaller regions provide high enough accuracy yet validation error is too high, i.e. it does not regularize well

Moving on to statistical approach, an ANN with different number of neurons was tested. The optimal number of neuron was found out to be 20 (varied from 5 to 100). The results were decent compared to other methods(refer to 7).

The second statistical method used was the use of CNN. After analysing different architectures, the best results are shown here (refer to figure 8).

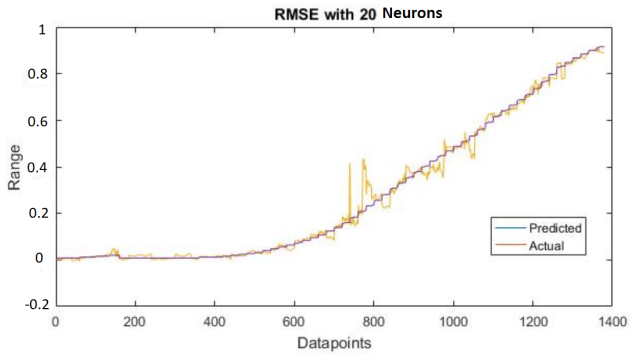

Fig. 7. The best result for manually extracted features can be seen by ANN with 20 hidden neurons in a single hidden layer

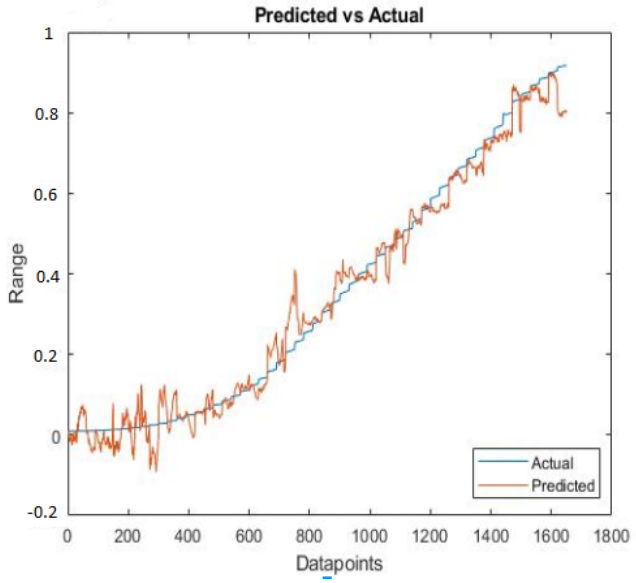

Fig. 8. On proper tuning of the network architecture we get a robust design which regularizes well as well as provides a decent estimate of the range

TABLE II
ERROR RESULTS

Method	RMSE(%)
Linear Regressor	10.33
Linear SVM	9.24
Non-Linear SVM	8.47
Decision Tree	1.60
ANN	2.84
CNN	4.14

*For CNN, best result is shown.

The table II and table III list the key results.

TABLE III
RESULTS OF GEOMETRIC METHOD

Calculated	116 cm	133 cm	142 cm
Actual	115 cm	123 cm	131 cm

V. CONCLUSION

In this paper, we have shown how well various methods that can be used for range estimation from an image perform. This helps us to know the criteria for choosing a particular method for task specific operations. The results of various regressors were compared to give an overall idea about each method. One can easily try out these regressors for their specific task. The versatility of deep learning helps to extend the problem statement to great limits. However the discussed method fails when there is scarcity of training data or change in the data on which it is trained, this drawback can be thought of, as if the tracker's location is changed, the method will fail to generalize. Implementation of the system in real-time required forward propagation alone, and the algorithm has to be optimized; other future work may include getting better optimised architecture and extending the problem statement to more general conditions including weather and atmospheric effects on feature extraction. There is also a prospect of piece-wise regressors i.e. depending on the performance of regressors in each range interval we can implement different algorithms to further enhance and improve the performance of our regressor.

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