

April 2014

## C&R Tree based Air Target Classification Using Kinematics

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### Recommended Citation

Garg, Manish and Singh, Upasna (2014) "C&R Tree based Air Target Classification Using Kinematics," *International Journal of Computer and Communication Technology*. Vol. 5 : Iss. 2 , Article 2.  
Available at: <https://www.interscience.in/ijcct/vol5/iss2/2>

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# C&R Tree based Air Target Classification Using Kinematics

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**Abstract** - Since the improvement in Anti Radar Material technology and stealth technology grows, there are immense counter measures that have opened to deny such technologies for classification to the adversary. At the same time it is observed that radar is continuously tracking the air target. This track data represents the kinematics which can be efficiently manipulated for effective classification without being deceived. The present study uses decision tree based classifier, specifically Classification and Regression Tree (CRT) algorithm over certain significant feature vectors. It classifies the data set of an air target into a target class where feature vectors are derived from the Radar Track Data using Matlab code. The work presented here aims to assess the performance of CRT. Although the methods and results presented here are for Air Target Classification, they may give insight for other applications.

**Keywords**- Air Target Classification, CRT Classifier, Feature Vectors, Kinematics, Radar Track data.

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## I. INTRODUCTION

The surveillance of air space is integral to civil and security applications. In defence application, depending upon the security scenario, an unidentified air target is tracked and classified for threat evaluation and proper weapon assignment. The problem of classification and identification of aircraft which do not broadcast their own identity is of recurring interest. For non cooperative target recognition, considerable effort has been expended. Unfortunately, no accurate and practicable technique has been developed which is appropriate to small "real-time" systems (see [1]-[9] and references cited therein).

Various approaches are analysed- Use of polar metric data, one dimensional High Resolution Range Profiles(HRRPs) or two dimensional Inverse Synthetic Aperture Radar(ISAR). Most of the work has been undertaken in the high frequency regime and involves extraction of scattering centers for identification of targets. [1] examine a technique which employs the statistics of the tracking data used by many missile seekers and which creates a cross-range target structure map that can be expressed as a function of the target's down-range extent. [2] examines Radar target identification based on High Resolution Range Profiles (HRRPs) because of its reduced complexity than those using two-dimensional (2-D) ISAR images .Specialized technology like ISAR processing makes systems uneconomical. These techniques rely on high frequencies, characterized by speculation. The newer

stealth technology, which uses airframe shaping and Radar Absorbent Material (RAM) in aircraft design, is likely to make identification of targets at such frequencies difficult.

In [3,4], a Bayesian approach was used as an inference engine for their Joint Tracking and Classification (JTC) application using passive radars. Radar cross section (RCS), which is also a function of target position, orientation and target class, was chosen to implement target recognition. [5] exploits aircraft-class specific kinematics to assess the tracked target's likelihood. Generalized Pseudo-Bayesian (GPB) class of algorithms is used for a suboptimal approximation. [6] shows a neural network approach is used to recognize and classify airborne targets. According to [7], the suggested methodology broadly features data acquisition, feature extraction and classification. In [8] Challa and Pulford argue that Target tracking and target classification are fundamentally linked. As we have seen from [1-8] separate suite of sensors or sensor models and techniques are used to solve them. For example, target tracking is usually performed using data from kinematic sensors (e.g. radar) while target classification is usually performed using data from identity or attribute sensors (e.g. electronic support measure (ESM), inverse synthetic aperture radar (ISAR), high resolution radar).

In this paper, we quantify kinematic information from radar track data, as received from a radar tracker, and use it to assess the likelihood of a tracked target. Aircraft have unique physical attributes that characterize

their angular and translational motion due to applied input forces. The analysis of these unique significant features leads to the classification. This paper is covered in six sections. Section 1 covers the literature survey associated with the problem and defining the problem statement. Section 2 introduces certain basic elements employed. Section 3 covers the proposed methodology followed by Section 4 Experimental Analysis, Section 5 Results and Conclusion in section 6.

## II. BASIC CONSTRUCTS

**Radar Track Data:** A radar tracker is a component of a radar system, or an associated command and control (C2) system that associates consecutive radar observations of the same target into tracks. The sequence of data, as received from a radar tracker, is known as Radar track Data.

**CRT Classifier:** C&RT, a recursive partitioning method, builds classification and regression trees for predicting continuous dependent variables (regression) and categorical predictor variables (classification). The classic C&RT algorithm was popularized by Breiman et al. (Breiman, Friedman, Olshen, & Stone, 1984; Ripley, 1996).

## III. PROPOSED METHODOLOGY

Different classes of aircraft (e.g. fighter plane, commercial passenger aircraft) differ in their geometry, size, and flight envelope and in particular in their maneuvering capabilities. The acceleration capabilities of various targets can most naturally be incorporated into the target's discrete-time dynamical state equation as input terms [8], while the rotational (angular dynamical) properties of aircraft can be incorporated as extra states [9]. The proposed methodology shown in Figure 3.1 is explained as:

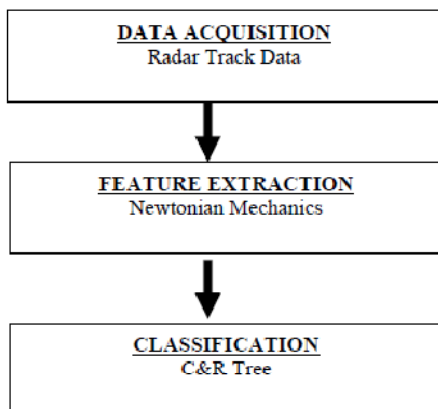


Fig 3.1: Proposed Methodology

**A. Data Acquisition.** The dynamical behavior of the target is embedded in the observed radar data and extraction of this information is a basis for target classification. The data received is a sequence of plots made in space. It may be acquired in any form of coordinates, say polar metric, Earth Centered Earth Fixed (ecef), Cartesian etc.

**B. Feature Extraction.** When an aircraft can be assumed to be a rigid body moving in space, its motion can be considered to have six degrees of freedom (Three axes x-y-z for translational move and moment about these three axes for rotational move). By applying Newton's Second Law to the rigid body, the aircraft equations of motion can be established in terms of translational and angular accelerations which occur as a consequence of forces and moments being applied to the aircraft. Sensor data are discrete time measurements thus motivating a discrete time approximation of the linear equations of motion. Thus, we consider the aircraft kinematic model as described by the linear discrete time system

$$X_{(k+1)} = fn(X_k) \tag{1}$$

where the state X is a 4 dimensional vector i.e. (x,y,z,t). Using Newtonian mechanics, the translational movement is analyzed in terms of rate of change of space wrt time.

$$[V_x, V_y, V_z] = d/dt [x, y, z], \tag{2}$$

$$V = (V_x + V_y + V_z)^{1/2} \tag{3}$$

where V denotes the velocity and the subscript denotes the component along a axes.

This would give the relative velocity of the object about the three axes. Further analysis in terms of rate of change of velocity wrt time calculates the acceleration along the 3-axes and at the same time illustrates the maneuver of the target.

$$[A_x, A_y, A_z] = d/dt (V_x, V_y, V_z) \tag{4}$$

$$A = (A_x + A_y + A_z)^{1/2} \tag{5}$$

where A denotes the acceleration and the subscript denotes the component along a axes.

Further examination of the three dimensional trajectory of the target, its Curvature at any instance is calculated. For a parametrically defined space curve in three-dimensions given in Cartesian coordinates (x(t),y(t),z(t)), the curvature is

$$\kappa = \frac{\sqrt{(z''y' - y''z')^2 + (x''z' - z''x')^2 + (y''x' - x''y')^2}}{(x'^2 + y'^2 + z'^2)^{3/2}} \tag{6}$$

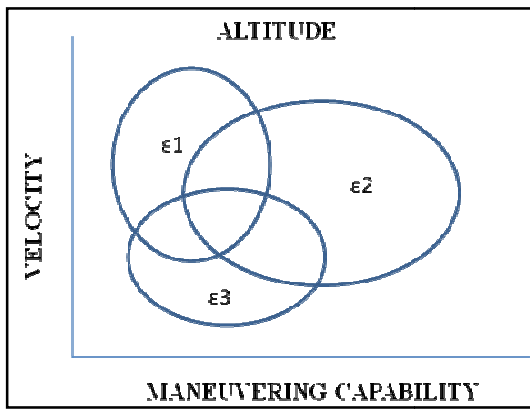
where the prime denotes differentiation with respect to time  $t$ .

[10] has brought to light the maneuvering capability of a air target in terms of its capability to accelerate. To examine the relationship between the velocity at which an air target can make a turn, the centrifugal acceleration  $\epsilon$  is calculated

$$\epsilon = V^2/\kappa \tag{7}$$

Eventually, the set of feature vectors that is contemplated to be significant to classify the air target is given as follows:

$$\epsilon = [z, V_x, V_y, V_z, A_x, A_y, A_z, V, A, \kappa, \epsilon] \tag{8}$$



Thus the flight state of an air target depicted as  $\epsilon$  can be seen as a function of its altitude, velocity and maneuvering capability. It is also seen in Figure 3.2 that although the flight envelop of an aircraft is bound by its features, there are flight envelopes overlapping.

**C. Classification.** Further step in the target identification process concerns the transformation of a set of entity attributes into a label describing the target identity. Algorithms are often based on pattern recognition techniques such as rule and frame based expert systems, fuzzy systems, artificial neural networks or the use of techniques such as Bayesian networks and Dempster- Shafer theory. Davis,s law states that ‘ For every tool there is a task perfectly suited to it (Davis and King,1977).

The purpose of the analyses via tree-building algorithm, Classification and Regression Tree (CRT) is to determine a set of if-then logical (split) conditions that permit accurate classification of cases. The purpose of the analysis is to learn how we can discriminate between the types of Air Target based on the measures of altitude, velocity and acceleration along the three axes, curvature of its path and centrifugal acceleration.

Discriminant function analysis will estimate several linear combinations of predictor variables for computing classification scores (or probabilities) that allow the user to determine the predicted classification for each observation. A classification tree will determine a set of logical if-then conditions (instead of linear equations) for predicting or classifying cases instead.

Tree classification techniques, when they "work" and produce accurate predictions or predicted classifications based on few logical if-then conditions, have a number of advantages over many of those alternative techniques.

1. Simplicity of results. Simplicity is useful for purposes of rapid classification of new observations.
2. Tree methods are nonparametric and nonlinear. The final results of using tree methods for classification or regression can be summarized in a series of (usually few) logical if-then conditions (tree nodes). Therefore, there is no implicit assumption that the underlying relationships between the predictor variables and the dependent variable are linear, follow some specific non-linear link function, or that they are even monotonic in nature.

**IV. EXPERIMENTAL ANALYSIS**

**A. Target Classes identified for classification:**

1. Unmanned Aerial Vehicle.
2. Rotor Wing Aircraft,
3. Transport Aircraft,
4. Fighter Aircraft,

**B. Data Sets used:**

Four Samples of each class are used. Each sample has four attributes: [time,x,y,z] i.e. Radar Track Data which is shown in Table 4.1 gives the instantaneous location of air target in space. Each sample has more than 1000 records. Here the [x,y,z] coordinates are given in Earth-Centered, Earth-Fixed (ecf) format.

*Table 4.1: Sample Radar Track Data*

Time	x	y	z
0	1324333	5395816	3123928
1	1324239	5395846	3123917
2	1324145	5395876	3123905
...	.....	.....	.....
1005	1323862	5395966	3123871

Using Matlab code, the RTD is converted to feature vectors as discussed in (8) section III. Here coordinate reference system used is ENU (East, North, Up).

Similarly, all the samples are converted to feature vectors as shown in Table 4.2. For classification, we have used IBM SPSS Modeler version 14.1.

Table 4.2: Sample feature vectors as derived from Radar Track Data

Altitude	Vx	Vy	Vz	Ax	Ay	Az	V	A	€
650.2329	98.4140	-13.0771	0.818962	0	-0.87184	-0.4897	99.2824	1	0.993843
652.4208	98.4140	-13.0771	0.818962	3.64E-12	-0.87184	-0.48979	99.2824	1	0.993843

**Experiment 1.** Input to CRT model is a mixed sample of all four classes containing all 9 input attributes and 10<sup>th</sup> target field class. It is seen in Figure 4.1 that velocity is the most important field.

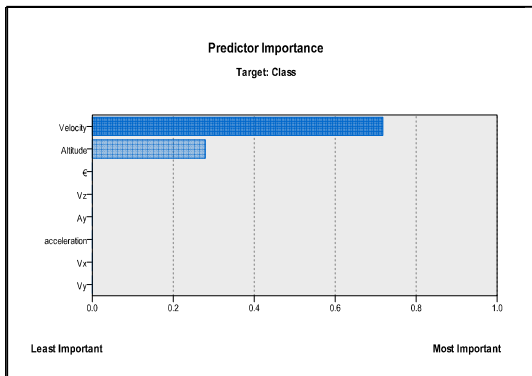


Figure: 4.1 Predictor analysis showing inter se importance of the feature vectors for Experiment 1

In addition to altitude, using acceleration and z component of velocity model gives following results for output field Class

Comparing \$R-Class with Class

Correct	14,811	100%
Wrong	0	0%
Total	14,811	

The rules are given as follows:

- Altitude  $\leq 4451.996$  [ Mode: 2 ]
- Altitude  $\leq 456.377$  [ Mode: 2 ]
- Vz  $\leq 2.132$  [ Mode: 2 ]  $\Rightarrow 2$
- Vz  $> 2.132$  [ Mode: 4 ]  $\Rightarrow 4$
- Altitude  $> 456.377$  [ Mode: 1 ]
- Altitude  $\leq 1722.983$  [ Mode: 1 ]
- acceleration  $\leq 1.866$  [ Mode: 1 ]
- Vz  $\leq 3.232$  [ Mode: 1 ]  $\Rightarrow 1$
- Vz  $> 3.232$  [ Mode: 4 ]  $\Rightarrow 4$
- acceleration  $> 1.866$  [ Mode: 4 ]  $\Rightarrow 4$
- Altitude  $> 1722.983$  [ Mode: 4 ]  $\Rightarrow 4$
- Altitude  $> 4451.996$  [ Mode: 3 ]  $\Rightarrow 3$

**Experiment 2.** Velocity and its horizontal components are withheld from the Input to CRT model. Now it is seen in Figure 4.2 that altitude is the most important field.

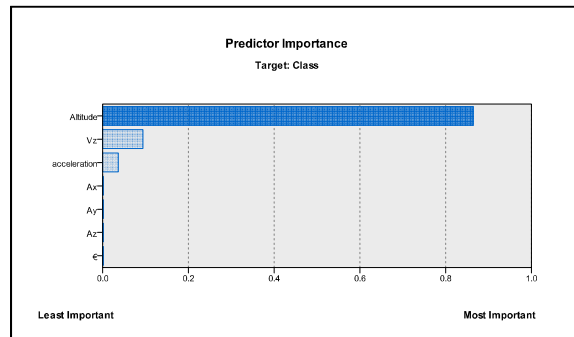


Figure: 4.2 Predictor analysis showing inter se importance of the feature vectors for Experiment 2

In addition to altitude, using acceleration and z component of velocity model gives following results for output field Class

Comparing \$R-Class with Class		
Correct	14,225	96.04%
Wrong	586	3.96%
Total	14,811	

The rules are given as follows:

Altitude  $\leq$  4451.996 [ Mode: 2 ]  
 Altitude  $\leq$  456.377 [ Mode: 2 ]  
 Vz  $\leq$  2.132 [ Mode: 2 ]  $\Rightarrow$  2  
 Vz  $>$  2.132 [ Mode: 4 ]  $\Rightarrow$  4  
 Altitude  $>$  456.377 [ Mode: 1 ]  
 Altitude  $\leq$  1722.983 [ Mode: 1 ]  
 acceleration  $\leq$  1.866 [ Mode: 1 ]  
 Vz  $\leq$  3.232 [ Mode: 1 ]  $\Rightarrow$  1  
 Vz  $>$  3.232 [ Mode: 4 ]  $\Rightarrow$  4  
 acceleration  $>$  1.866 [ Mode: 4 ]  $\Rightarrow$  4  
 Altitude  $>$  1722.983 [ Mode: 4 ]  $\Rightarrow$  4  
 Altitude  $>$  4451.996 [ Mode: 3 ]  $\Rightarrow$  3

**Experiment 3.** Now even the horizontal component of velocity is withheld from the Input to CRT model. Now it is seen in Figure 4.3 that altitude is the most important field used for classification.

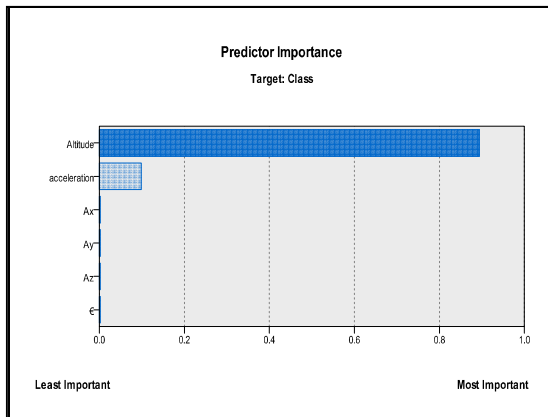


Figure :4.3 Predictor analysis showing inter se importance of the feature vectors for Experiment 3

In addition to altitude using acceleration, model gives following results for output field Class Comparing \$R-Class with Class.

Correct	13,755	92.87%
Wrong	1,056	7.13%
Total	14,811	

The rules are given as follows:

Altitude  $\leq$  4451.996 [ Mode: 2 ]  
 Altitude  $\leq$  456.377 [ Mode: 2 ]  
 acceleration  $\leq$  1.866 [ Mode: 2 ]  $\Rightarrow$  2  
 acceleration  $>$  1.866 [ Mode: 4 ]  $\Rightarrow$  4  
 Altitude  $>$  456.377 [ Mode: 1 ]  
 Altitude  $\leq$  1722.983 [ Mode: 1 ]  
 acceleration  $\leq$  1.866 [ Mode: 1 ]  $\Rightarrow$  1  
 acceleration  $>$  1.866 [ Mode: 4 ]  $\Rightarrow$  4  
 Altitude  $>$  1722.983 [ Mode: 4 ]  $\Rightarrow$  4  
 Altitude  $>$  4451.996 [ Mode: 3 ]  $\Rightarrow$  3

**Experiment 4.** Now even the altitude is withheld from the Input to CRT model. Now it is seen in Figure 4.4 that acceleration is the most important field used for classification based on CRT.

In addition to acceleration using centripetal acceleration, model gives following results for output field Class

Comparing \$R-Class with Class		
Correct	7,578	51.16%
Wrong	7,233	48.84%
Total	14,811	

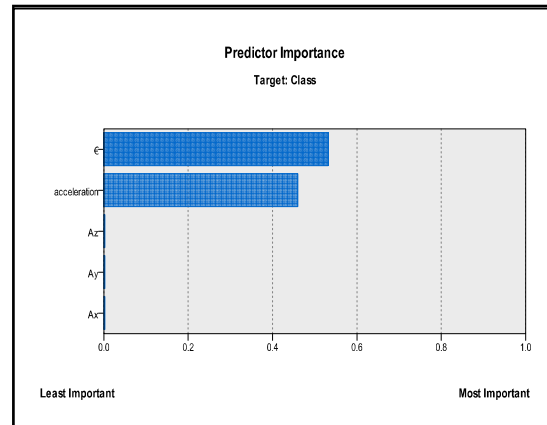


Figure : 4.4 Predictor analysis showing inter se importance of the feature vectors for Experiment 4

The rules are given as follows:

acceleration  $\leq$  1.751 [ Mode: 2 ]  
 $\epsilon \leq$  0.880 [ Mode: 3 ]  
 $\epsilon \leq$  0.309 [ Mode: 2 ]

acceleration  $\leq 0.000$  [ Mode: 1 ]  $\Rightarrow 1$

acceleration  $> 0.000$  [ Mode: 2 ]  $\Rightarrow 2$

$\epsilon > 0.309$  [ Mode: 1 ]

$\epsilon \leq 0.358$  [ Mode: 1 ]  $\Rightarrow 1$

$\epsilon > 0.358$  [ Mode: 3 ]

$\epsilon \leq 0.507$  [ Mode: 3 ]  $\Rightarrow 3$

$\epsilon > 0.507$  [ Mode: 1 ]  $\Rightarrow 1$

$\epsilon > 0.880$  [ Mode: 2 ]

$\epsilon \leq 0.924$  [ Mode: 2 ]  $\Rightarrow 2$

$\epsilon > 0.924$  [ Mode: 2 ]

$\epsilon \leq 0.970$  [ Mode: 3 ]  $\Rightarrow 3$

$\epsilon > 0.970$  [ Mode: 2 ]  $\Rightarrow 2$

acceleration  $> 1.751$  [ Mode: 4 ]  $\Rightarrow 4$

## V. RESULTS

The following observations are made:

1. It is observed from the serial no.6 and 7 of Table 5.1 that inclusion of field centripetal acceleration in presence of z component of velocity and acceleration has no affect on the result. Since this field is a function of velocity and acceleration, it can be omitted from the computation.
2. To handle the deception, a decision tree will have to ignore velocity and altitude fields. In that case relying on z component of velocity and acceleration is able to classify 66.57% correct

Table 5.1: Comparison of results showing various input fields and their respective classification correctness

	Input fields	Correct	Wrong
1.	$V_x, V_y, V_z, V, A_x, A_y, A_z, A_z, \epsilon$	100%	0%
2.	$V_z, A_x, A_y, A_z, A_z, \epsilon$	96.04%	3.96%
3.	$A_x, A_y, A_z, A_z, \epsilon$	92.87%	7.13%
4.	$A_x, A_y, A_z, A, \epsilon$	51.16%	48.84%
5.	$A_x, A_y, A_z, A$	40.56%	59.44%
6.	$A_x, A_y, A_z, A, V_z, \epsilon$	67.13%	32.87%
7.	$A_x, A_y, A_z, A, V_z$	67.13%	32.87%
8.	$A_z, A, V_z$	67.13%	32.87%
9.	$A_z, V_z$	66.57%	33.43%

## VI. CONCLUSION

The information from the radar, i.e. its location in space at an instant, can provide indications of the target type. It is observed that the flight state i.e. its altitude, velocity and acceleration at an instant is strictly bound by a flight envelop. Although these envelops are overlapping in limited dimension scenario there are certain peculiar characteristics, of the target class, that are able to classify air target. This study attempts to identify dimensions which do not overlap and distinctly classifies the target. It concludes that in case a target is displaying its characteristics within the normal behavior pattern, the C&RT classifier is able to classify with 100% confidence. However if the target plans a deception, we need to ignore its altitude and horizontal velocity and acceleration components. In that case the correctness of classification reduces to 67%.

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