Progress In Electromagnetics Research C, Vol. 21, 243–255, 2011

CLASS IDENTIFICATION OF AIRCRAFT BY MEANS OF ARTIFICIAL NEURAL NETWORKS TRAINED WITH SIMULATED RADAR SIGNATURES

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Abstract—Non-Cooperative Target Identification (NCTI) of aircraft from radar measurements is a formidable problem that has drawn the attention of engineers and scientists over the last years. NCTI techniques typically involve a database with a huge amount of information from different known targets and a reliable identification algorithm able to highlight the likeness between measured and stored data. This paper uses High Resolution Range Profiles produced with a high-frequency software tool to train Artificial Neural Networks for distinguishing between different classes of aircraft. Actual data from the ORFEO measurement campaign are used to assess the performance of the trained networks.

1. INTRODUCTION

One of the main concerns in the Air Forces during the last years has been the development of a reliable identification system that minimizes fratricide between allied forces. The different techniques that have been researched to solve this problem may roughly be divided into two classes [1]: cooperative and non-cooperative techniques. Cooperative techniques (often referred to as Identification Friend or Foe-IFF-techniques) are already operational. In fact, most fighter aircraft are equipped with transponder systems answering to authorized interrogations by transmitting a predetermined coded signal. By this, friendly aircraft can be identified (if the IFF is working properly) but positive identification of hostile or neutral aircraft is not possible.

In principle, this task could be achieved by the so-called Non-Cooperative Target Identification/Recognition (NCTI/R) techniques

Received 2 March 2011, Accepted 17 May 2011, Scheduled 27 May 2011
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based on radar, which rely on a comparison between the measured target signature and a reference database [2]. The main task of NCTI is the development of an identification (ID) system capable of making a reliable classification of aircraft into different groups (friendly, hostile or neutral), classes (aircraft that have been designed for a similar use, e.g., civilian airliner, fighters or unmanned aerial vehicles) or even types (aircraft that belong to a same class, e.g., Boeing 747, Boeing 767, Airbus 310, etc.).

NCTI by means of radar can be mainly accomplished by Jet Engine Modulation (JEM), High Resolution Range Profiles (HRRPs) or Two-Dimensional Inverse Synthetic Aperture Radar (2D-ISAR) images [3]. For any of these alternatives, however, one of the main concerns is the generation of the database with known information of different targets.

Among the different possibilities to fulfill this task, such as measurement campaigns of flying aircraft, scale model measurements or predictions obtained by electromagnetic software tools, the latter seems to be the most feasible option, as it requires lower cost and permits an easier way to obtain information of all the possible targets, aspect angles and configurations. In this context, this paper presents part of the Detectability and Electronic Warfare Laboratory (INTA) research activities regarding the classification of different targets based on their actual in-flight measurements, using a database populated only with predicted HRRPs obtained with FASCRO, a high frequency Radar Cross Section (RCS) prediction code [4].

Range profiles can be seen as a 1D image of an aircraft, where the parts of the aircraft that mainly reflect the radar radiation, called scatterers, project their reflection onto the Line Of Sight (LOS). A HRRP for a determined aspect angle can be obtained after transforming to the time-domain (by means of a Fourier transform) the RCS response of the target at different controlled frequencies [5]. Usually, windowing functions are applied before Fourier transforming to reduce spectral leakage, although they cause a reduction in resolution.

HRRPs are different for each type of aircraft, so they are suitable data for aircraft classification [6–11]. However, profiles depend strongly on target aspect angle and a large data set is needed. Consequently, the design of an identification system capable to manage this huge quantity of changeable information is a challenging task. Artificial Neural Networks (ANNs) have demonstrated their applicability on different complex fields, even NTCI [12, 13].

This manuscript introduces a class ID proposal based on ANNs whose inputs are actual data but previously trained only with simulated range profiles. Apart from class identification, a main candidates list for type ID is also achieved. The system is tested with actual HRRPs obtained from the ORFEO measurement campaign. The two following sections provide information about measurement and simulation parameters and data processing, whereas Section 4 describes the networks employed and Section 5 the results obtained.

2. DATA SOURCE

2.1. Actual Data

The North Atlantic Treaty Organization (NATO) performs different research activities under its Research and Technology Organisation (RTO). Over the years, part of this research has been focused on high resolution radars and some measurement campaigns of actual flying aircraft have been conducted. This is the case of the data used in this communication, which comes from the ORFEO measurement campaign of civilian airliners, held in 1995 and obtained with the FELSTAR radar (stepped-frequency S-band radar owned by TNO-FEL and located in The Hague, The Netherlands) [14]. This measurement campaign was carried out as part of the RTO-SET-040 Task Group activity and up to 17 different civilian airliners of opportunity were measured.

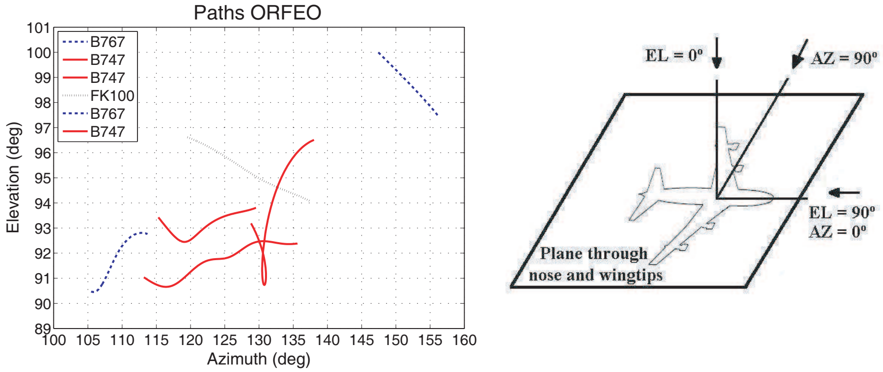
For this work, the targets under study are a Fokker 100 (266 profiles), a Boeing 747–400 (959 profiles) and a Boeing 767 (269 profiles), which follow different paths (Figure 1(a)). The orientation criteria and coordinate system are shown in Figure 1(b) and, according to this and Figure 1(a), these aircraft were illuminated a bit below the plane through nose and wingtips, and between side-on and tail-on aspect angles.

The main measurement parameters used in this campaign are shown in Table 1. These parameters were considered in order to guarantee two main goals: to allow any civilian target to be within the unambiguous range and to improve the robustness for target radial motions. In this sense, the maximum unambiguous range (R_u) and range resolution (ΔR) for a stepped-frequency radar are given by Equations (1) and (2),

$$R_u = \frac{c}{2\Delta f} \tag{1}$$

$$\Delta R = \frac{c}{2N\Delta f} = \frac{c}{2\beta} \tag{2}$$

where c is the speed of light.



(a) (b)

Figure 1. (a) Paths followed by the targets under study regarding ORFEO campaign. Boeing 747 (solid line), Boeing 767 (dashed line) and Fokker 100 (dotted line). (b) Coordinate system and orientation criteria.

Table 1. Orfeo campaign waveform parameters.

Frequency		S-Band
Waveform		Stepped frequency
Polarization		Vertical
Bandwidth	β	453.6 MHz
N. of pulses	N	324
Frequency step	Δf	1.4 MHz
Unambiguous range	R_u	107.5 m
Range resolution	ΔR	0.33 m

2.2. Synthetic Data

FASCRO is the code employed to predict the RCS of the targets used to generate the HRRPs for this paper. It is a software tool based on high frequency techniques (Physical Optics, PO, and Physical Theory of Diffraction, PTD) that calculates the monostatic RCS of electrically large complex targets. It works directly with Computer-Aided Design (CAD) geometries modelled by Non-Uniform Rational B-Splines (NURBS) surfaces [15], which allows good fitting to the actual geometry of the target with less entities, and avoids the generation of artificial edges, typical in faceted models. Figure 2 shows the civilian CADs modelled by NURBS used in this work.

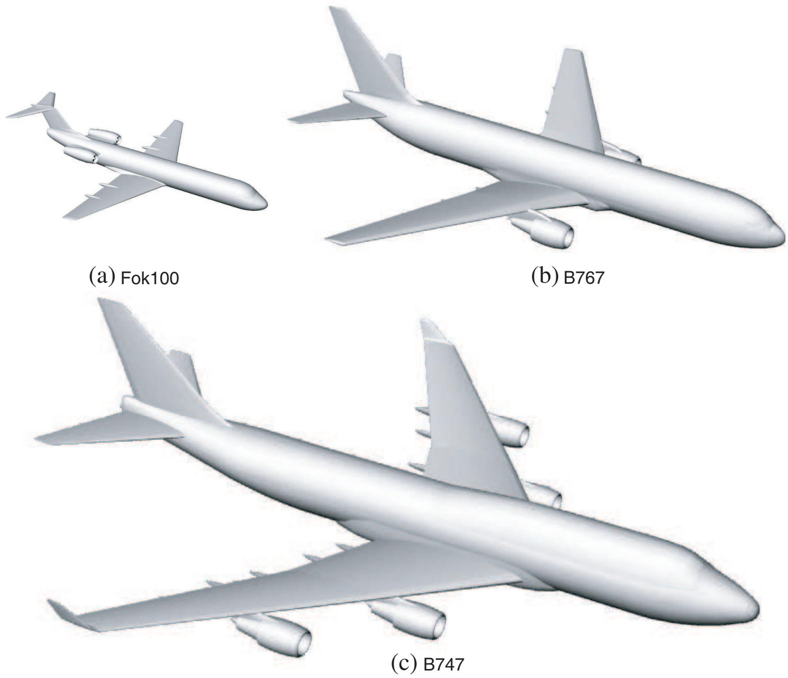


Figure 2. NURBS CAD models (same scale ratio for the three models).

Due to the asymptotic nature of the code, significant responses from small or resonant size parts of the targets are not well treated by FASCRO [16]. Therefore, antennas, inlets, exhaust pipes, cavities, small protuberances, ... are not included in the models used here. Besides, although each surface of the model can be assigned a different material in FASCRO, the simulations are run considering all surfaces as Perfect Electric Conductor (PEC). It may sound strange, but the aim is not to obtain excellent predictions that could perfectly match the measurements. To do so, rigorous techniques such as the Method of Moments — MoM — or Finite Element Method — FEM — could be tried, although it would take a huge amount of time [17]. Indeed, the objective is to generate a database in a reasonable time with HRRPs good enough to being able to distinguish different targets.

In this work, the synthetic database was populated with five different targets (see Table 2), belonging to two different classes: 3 civilian airliners (Fokker 100, Boeing 747–400 and Boeing 767) and 2 UAVs developed at the Institute and coded here as UAV1, with

Table 2. Brief description of the targets that populate the synthetic database.

Type	Class	Height (m)	Length (m)	Wingspan (m)
Boeing 747	Civilian	19.41	70.66	64.44
Boeing 767	Civilian	15.85	54.94	59.64
Fokker 100	Civilian	8.50	35.53	47.57
UAV1	UAV	1.44	8.20	12.50
UAV2	UAV	1.09	4.00	5.81

12.5 m wingspan and UAV2, with 5.81 m wingspan. These aircraft were simulated for the paths shown in Figure 3: three paths with constant elevation angle (92, 96 and 100 degrees) and each one with 45 degrees azimuth variation. Each path consists of 1894 points (one point is a profile) meaning that the azimuth step is 0.0243 degrees. The choice of this azimuth step is due to the fact that these data will be used to perform ISAR images in a future work and such azimuth variation is the most suitable for that objective. Moreover, the more profiles the better for training the ANN. Therefore, the simulated database is finally populated by 28410 profiles (3 paths $\times$ 1894 point each path $\times$ 5 aircraft).

It can also be seen in Figure 3 that the simulated paths do not mimic the actual paths from the measurement campaign, but, instead, try to cover an angular area which almost contain all of them. This is because a hypothetical future complete database of simulated data could not contain all the possible aspect angles of a sphere and, therefore, an approach with selected cuts makes more sense. Finally, all the targets under study were simulated for the above-mentioned synthetic paths considering the same parameters used in the measurement campaign (Table 1).

3. DATA PROCESSING

As said, some parts and effects are not taken into account in the simulations and, therefore, differences between synthetic and actual data are expected. However, the aim is to be able to discriminate among classes, and, for that purpose, discrepancies between an actual and a synthetic profile of the same aircraft should be less than differences between an actual profile of an aircraft and synthetic ones of other targets.

To accomplish this, proper pre-processing is necessary to enhance

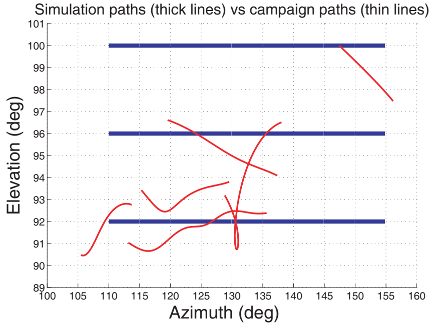


Figure 3. Simulated paths (thick lines) cover an angular area which almost contain all actual paths (thin lines).

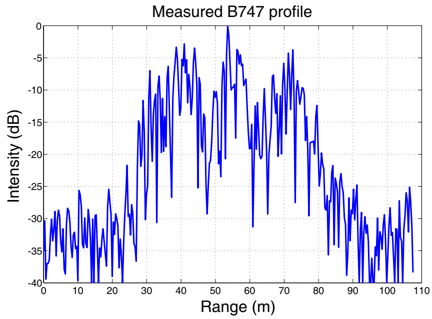


Figure 4. Measured B747 profile as a result of a typical processing to generate HRRPs.

the likeness between actual and synthetic data. First, a threshold level must be estimated for both measured and predicted profiles in order to minimize the effect of clutter and noise. Then, the prominent peaks as well as the relative distance among them and their intensity are extracted. All these features will be used to produce more suitable profiles just with these information.

This discrimination between useful and useless information to generate appropriate input data is very important, since ANNs must be trained just with information that can characterize a single output during the training process, which is a feature of supervised learning. If the ANN is fed with complete profiles with no pre-processing during its training, it will not learn properly because both clutter and noise data will be considered as useful information for training stage, and consequently, incorrect outputs would appear.

3.1. Actual data

This subsection presents how measurements from ORFEO campaign have been processed with an example for a B747 profile. Figure 4 shows the profile as a result of a typical processing to generate HRRPs: a Hamming window is applied before a 256-point Fourier transform, the maximum is set to 0 dB and a dynamic range of 40 dB is assumed. Figure 5 is a normalization from 0 to 1 of the same profile, a typical requirement for ANNs inputs.

For this example, the target signal is located between 30 m and 80 m, approximately. However, the profile also contains clutter and noise information. To eliminate it, a threshold level must be estimated.

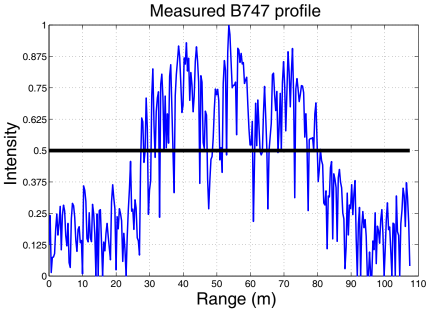


Figure 5. Measured B747 profile with its intensity normalized from 0 to 1. Thick line corresponds to the threshold level.

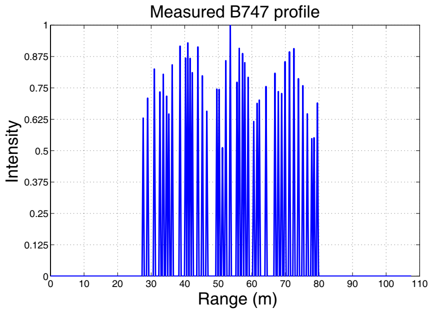


Figure 6. Useful information from a measured B747 profile suitable for the ANN.

This threshold will depend on both radar and measurement parameters and it can be set during the radar characterization process when it is designed to adapt the received signal to the ID system. In this work, the threshold level is estimated a posteriori (thick line in Figure 5), taking into account the ID system requirements described above: significant peaks, relative distance and intensity. Finally, only the peaks above this last threshold, keeping their original intensity level, are considered as inputs of the ANN (Figure 6).

3.2. Synthetic Data

The synthetic profiles are also processed following the above steps, but now, because simulations have no noise, the threshold level is clearly lower than the level used for measurements as can be seen in Figures 7 and 8.

4. ANN DESCRIPTION

The aim of this work is to test different ANN architectures where these suitable profiles are used as inputs. In the first one, the ANN has as many outputs as classes (two in this work: civilian airliners and UAVs). In the second one, the ANN has as many outputs as targets, 5 aircraft in this communication. There are up to 28410 simulated profiles, and they have been generated with Fourier transforms of 256, 324, or 512 points. Each ANN tried in this work is a multilayer perceptron with feedback propagation and 2 hidden layers, the first one with 16 neurons and the latter with 4 neurons (Figure 9).

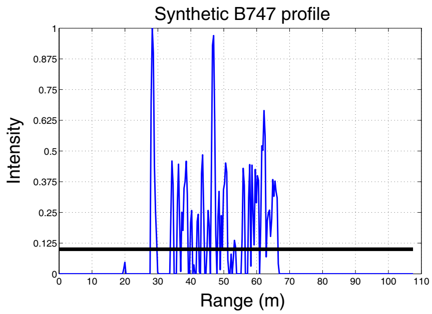


Figure 7. Simulated B747 profile with its intensity normalized from 0 to 1. Thick line corresponds to the threshold level.

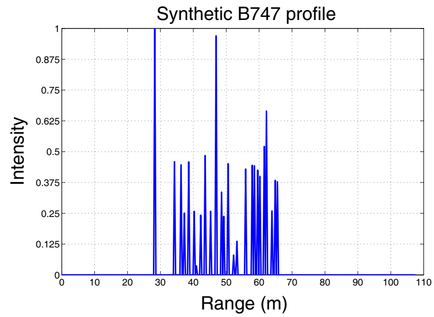


Figure 8. Useful information from a synthetic B747 profile suitable to feed the ANN.

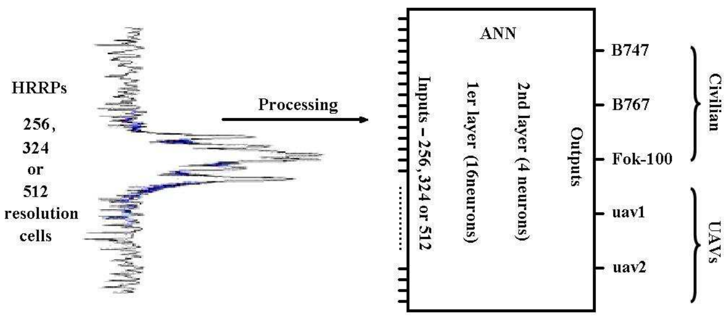


Figure 9. Network scheme with five outputs (one for each target). Another architecture, only with two outputs (one for each class), has been also checked.

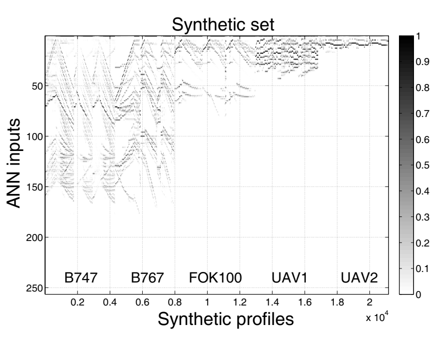


Figure 10. Training, validation and test set made by synthetic profiles.

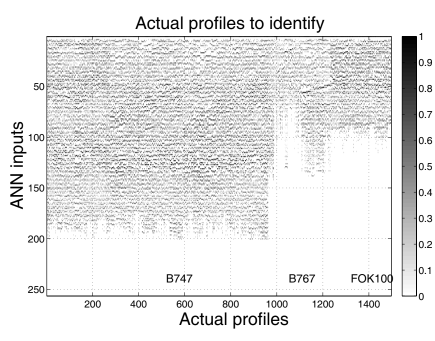


Figure 11. Measurement set in order to check the ANN behavior.

Figure 10 shows the processed simulated profiles used for training, validating and testing the networks, and the differences among classes can be appreciated. This process is done offline and should not be taken into account for the total ID time. After that, the ANN is ready to be fed with an actual measured profile (Figure 11) and, almost instantly, it will select an output with the chosen class or nominated target, depending on the architecture considered. Actual data are exclusively used for evaluating the capability of the ANNs for identification.

5. RESULTS

The results obtained with the proposed ID method are summarized on different confusion matrix shown in Table 3 to Table 6.

It can be appreciated that ANNs with 2 outputs, civilian airliners or UAVs, are able to distinguish between each class with high level of confidence, no matter the number of inputs, but no information on type ID is provided (Table 3).

Similarly, ANNs with 5 outputs, one for each target, are capable to perform class ID too, although class ID success drop slightly in some cases. Also, in this second configuration, additional type ID information is provided about the type of target (see Tables 4, 5 and 6). However, this information is not reliable to achieve type ID with enough level of confidence, but a list of likely candidates is obtained (this list consist of two target and they appear in bold face in each table). It can be seen that the actual aircraft is always part of

Table 3. Confusion matrix of ANNs with 2 outputs (columns) and different number of inputs.

256P	CIV	UAV	% CLASS ID
CIV	1494	0	100
324P	CIV	UAV	% CLASS ID
CIV	1494	0	100
512P	CIV	UAV	% CLASS ID
CIV	1494	0	100

Table 4. Confusion matrix of ANN with 256 inputs and 5 outputs.

256P	B747	B767	FK100	UAV1	UAV2	%TYPE ID	%CLASS ID
B747	**594**	**261**	56	29	19	61.94	94.99
B767	18	**159**	**83**	8	1	59.11	96.65
FK100	14	**96**	**123**	27	6	46.24	87.59

Table 5. Confusion matrix of ANN with 324 inputs and 5 outputs.

324P	B747	B767	FK100	UAV1	UAV2	%TYPE ID	%CLASS ID
B747	**83**	**876**	0	0	0	8.65	100.00
B767	51	**142**	**76**	0	0	52.79	100.00
FK100	27	**128**	**111**	0	0	41.73	100.00

Table 6. Confusion matrix of ANN with 512 inputs and 5 outputs.

512P	B747	B767	FK100	UAV1	UAV2	%TYPE ID	%CLASS ID
B747	**301**	**618**	37	2	1	31.39	99.69
B767	26	**168**	**49**	26	0	62.45	90.33
FK100	7	**120**	**122**	17	0	45.86	93.61

this list, proving that this method provides a reliable list of candidates. It is worth noting that the classification ratio depends slightly on the number of inputs, obtaining the best results when the number of inputs equals the number of resolution cells of the FELSTAR radar (324).

Then, taking into account these results, ANNs properly trained can be considered as an ID system capable of making a reliable aircraft classification into classes, and even to nominate a list of candidates for target type ID. However, a reliable type ID by means of synthetic HRRPs and ANNs has not worked in this case.

6. CONCLUSION

A class ID system for NCTI based on ANNs exclusively trained with simulated HRRPs has been introduced. For this particular study, the synthetic profiles belonged to five different aircrfats, grouped into 2 classes, civilian airliners and UAVs.

Then, the system has been tested with actual HRRPs from three different aircraft: Boeing 747, Boeing 767 and Fokker 100, which were obtained with an operative radar.

Although the ANNs behaviour strongly depends on several factors (training set, ANN architecture, number of inputs, hidden layers and outputs, number of neurons on each layer, training function, etc.), it can be appreciated that all the studied ANNs are able to distinguish the class with a high level of confidence. Therefore, ANN properly trained can be considered as an ID system capable of making a reliable aircraft classification into classes. Moreover, if ANNs are properly trained to distinguish among targets, they will be also capable to provide additional information about the type of target, so a list of main candidates for type ID can be obtained as well.

7. FURTHER WORK

The authors are working on different aspects of the ID method in order to improve the present work, i.e.,

- Research on different topologies: the number of neurons on each hidden layer, different networks parameters and even other types of ANN are being investigated more deeply to determine the optimum architecture for class ID purposes.
- Improvements on the database: additional electromagnetic simulations are been considered in order to increase the size of the synthetic database.
- Research on type ID: a complementary algorithm based on ISAR images is being developed in order to achieve a complete ID system, which will be able to obtain the type of target with a high level of confidence.
- Test the ANNs with other input targets: additional measurements of UAVs and small civilian jets are been acquired to fulfill this task.

ACKNOWLEDGMENT

The authors would like to thank the members of NATO-RTO SET-112 Task Group on "Advanced analysis and Recognition of Radar Signatures for Non-Cooperative Target Identification", for their helpful discussions and for the availability of actual data obtained through the measurements campaigns organized in the framework of this group. The work presented in this paper has been supported by INTA under the Electronic Warfare and Non-Cooperative Target Identification project.

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