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Challenges for Non-Cooperative Target Identification in a Bistatic Radar Configuration

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***Abstract*—NCTI ("Non-Cooperative Target Identification") in a monostatic radar configuration has been investigated extensively within the past years but classification in a bi-/ multistatic configuration does not seem to have obtained much attention to date. Some differences between monostatic and bistatic radar pose challenges to NCTI, which have to be met especially if monostatic and bistatic data or data with differing bistatic angles are to be compared. In this paper these challenges will be discussed and some classification procedures will be introduced. By means of data from turntable measurements of three distinct ground vehicles, which have been conducted at Fraunhofer FHR, the influence of different radar constellations on classification performance will be described.**

***Keywords*—Bistatic radar, classification procedures, NCTI, turntable measurements.**

I. Introduction

CLASSIFICATION of an object under consideration is of key importance for defence and homeland security applications. The main drawback of operational IFF ("Identification Friend – Foe")-systems is that they are only able to identify positively friendly targets; neutral or hostile targets will both be declared hostile. And also a friendly target whose IFF-transponder fails to reply for whatever reason will be declared hostile.

This drawback of IFF-systems has led to the development of NCTI ("Non-Cooperative Target Identification")-techniques, which in contrast to IFF aim to classify a target without active contribution of this target. Radar images of the target under consideration are generated, which can be compared with the entries of a database of radar images of possible targets to find the target's identity.

NCTI-techniques have been examined extensively in recent years and were considered to be reliable. In most of these cases a monostatic configuration was adopted. For reasons of energy efficiency, cost reduction and covert operation, with the latter being especially relevant in military or security-related scenarios, a bi- or multistatic configuration seems to be more appropriate for practical applications. But this means that existing NCTI-techniques have to be adjusted somehow for usage with a bi- or multistatic radar configuration. In this context, particular attention is paid to the question whether it is possible to use only monostatic radar data to build up a database for classification of bistatic data, which would simplify bistatic NCTI extraordinarily.

Based on real data of three different ground vehicles at different bistatic angles, first results concerning this question will be presented and other challenging aspects of bi-/ multistatic NCTI will be discussed in this paper.

II. Differences Between Mono- and Bistatic Radar with Relevance to NCTI

There are some differences between classification in a purely monostatic configuration and classification in a bi- / multistatic configuration that one should have in mind when reconfiguring a classifier for use with bistatic data. The root of these differences and the definition of bistatic radar at the same time is that the transmitter and the receiver are spatially separated. This spatial separation raises some questions, which have to be answered before a classifier can be adjusted for classification of bistatic data.

Since classification is highly dependent on target aspect angle the most obvious question is: What is the target's aspect angle? or more appropriately: *Where* is the target's aspect angle? This question is of particular interest if data with differing bistatic angles or bistatic and monostatic data are to be compared. There are three intuitively possible answers to this question, which all have their supporters:

1) Many scientists declare the target's bistatic aspect angle as seen from the bistatic bisector. Among them are Kell [1], Willis [2] and contributors to Willis/Griffiths [3]. This case is indicated by the red arrow in Fig. 1.
2) Some prefer to use the receiver azimuth as the target's aspect, for example Trizna and Xu [4] and Mishra and Mulgrew [5]. This case is indicated by the blue arrow in Fig. 1.

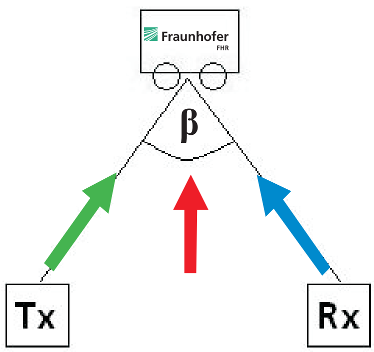

Fig. 1. Definitions of the bistatic aspect angle.

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3) Very seldom the target's aspect is defined as the transmitter azimuth, as Aldhubaib and Shuley [6] did. This case is indicated by the green arrow in Fig. 1.

So there is not a consistent definition of the target's aspect angle in a bistatic radar configuration in the open literature. Even though all these scientists surely had their reasons for defining the target's bistatic aspect angle as they did, none of them explained them or commented on the other two possible aspect angles. However, we will return to this topic later in Section 4 when it comes to the application of real data to different classifier concepts.

Bistatic radar data naturally comes along with an additional parameter: the bistatic angle. The consequential next question is: How can the bistatic angle be incorporated into a classification procedure, which has not been invented to deal with this additional parameter? There is no doubt that the bistatic angle must be accounted for somehow. Even if the target is measured at the same aspect angle, whose definition seems to be a matter of taste anyway, the data are assumed to look different for differing bistatic angles. The simplest solution to this problem seems to be the construction of a distinct classifier for any bistatic angle but it should be possible to find a less time-consuming solution.

To get one step closer to such a solution a better understanding of the scattering physics that produce the different-looking data for differing bistatic angles would be helpful. One possible cause of this data variation can be a change in RCS, which Kell [1] and Willis [2] trace back to three sources:

1) Changes in relative phase between scattering centre contributions, which are analogous to changes in relative phase caused by a change in aspect angle. Since the bistatic aspect angle is not consistently defined it is difficult to say how much of the change in relative phase is caused by a change in aspect angle and how much by a change in bistatic angle.
2) Changes in radiation from individual scattering centres since the amplitude and phase of radiation from a scattering centre possess an angular distribution. This means that the direction of backscatter from an individual scattering centre can be changed so that a different amount of energy is reflected in the direction of the receiver. Moreover, a simple scattering centre can even become a scattering centre showing multiple reflexions as the bistatic angle changes.
3) Changes in existence of scattering centres, which means appearance or disappearance of scattering centres as the bistatic angle is changed. This is typically caused by shadowing, for example, if one part of the target blocks the transmitter or receiver line of sight to a scattering centre.

Fig. 2. Ground vehicle #1: PALES experimental system.

Fig. 3. Ground vehicle #2: a dummy tank.

When we talk about a change in RCS then this generally means a degradation in RCS for small bistatic angles as the bistatic angle is increased. In fact, Kell [1] found that under weak conditions the bistatic RCS for a bistatic angle β is equal to the monostatic RCS measured on the bistatic bisector at a frequency lower by the factor $\cos(\frac{\beta}{2})$. Willis [2] and Willis/Griffiths [3] state that other radar characteristics like range and Doppler resolution are degraded by the factor $\cos(\frac{\beta}{2})$ for any bistatic angle, not only small ones. This means that the bistatic range cell is increased by the factor $\cos(\frac{\beta}{2})$ when compared to equivalent monostatic radar operation as measured on the bistatic bisector. However, this effect is assumed to be negligible for small bistatic angles.

For large bistatic angles close to 180° and wavelengths that are small compared to the target dimensions the effect of forward-scatter enhancement occurs, which means that the RCS of a target is increased compared to its monostatic RCS. But this enhancement in RCS comes with the limitation of severely degraded range and Doppler resolution, which makes classification virtually impossible [3].

In the remainder of this paper only classification problems with a small bistatic angle up to 15° will be treated so any possible effect of the bistatic configuration on range resolution will be neglected.

Fig. 4. Ground vehicle #3: an Opel Astra.

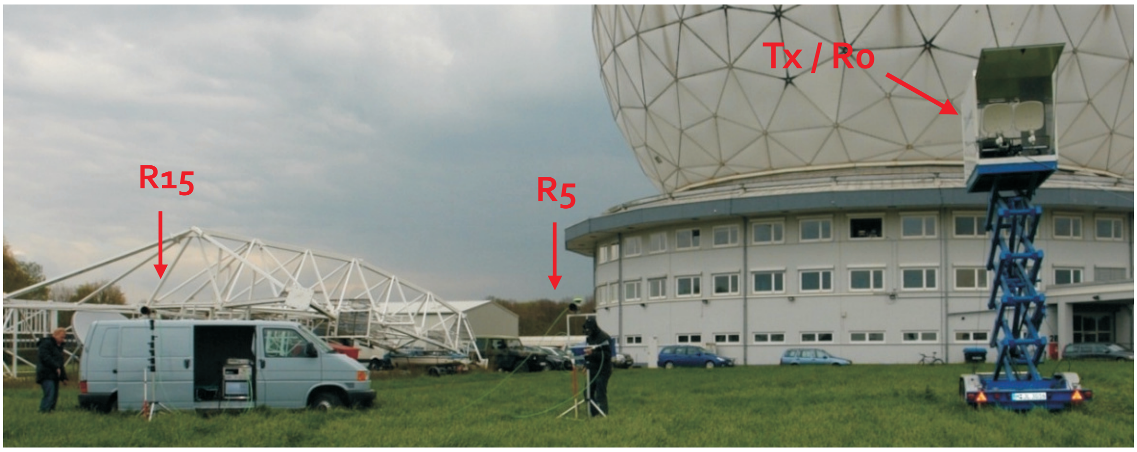

Fig. 5. Transmitter and receiving antennas.

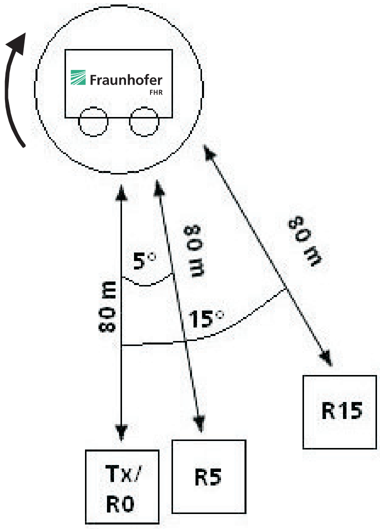

Fig. 6. Experimental setup (not to scale).

III. Description of the Experimental Setup

In April 2010 turntable measurements of three different ground vehicles were made at Fraunhofer FHR. The vehicles were the PALES experimental system developed at Fraunhofer FHR shown in Fig. 2, a dummy tank shown in Fig. 3 and an Opel Astra shown in Fig. 4.

At a distance of 80 m from the turntable the transmitter (Tx) was positioned, which transmitted a pulsed chirp with a bandwidth of 800 MHz at a centre frequency of 8.9 GHz. One receiving antenna (R0) was colocated with the transmitter in a monostatic configuration. A second (R5) and third (R15) receiving antenna were installed at bistatic angles of 5° and 15° respectively and both at a distance of 80 m from the turntable. Fig. 5 shows a photograph of the transmitter and receiving antennas and Fig. 6 shows a sketch not to scale of the experimental setup.

IV. Classification Experiments of the Bistatic Radar Data

The data gained from this trial and used for first classification experiments were HRR ("High Range Resolution")-profiles recorded in a monostatic radar configuration, at a bistatic angle of 5° and at a bistatic angle of 15°. As the training data only the monostatic data were used and the bistatic data were used for testing. For each classification procedure described below the data were derived from a rotation of the turntable of 10°, so they cover an azimuth span of the target of 10°. The target's aspect angle depends on the definition of the bistatic aspect angle of a target as discussed above. So, for each of the three possible definitions of the bistatic aspect angle the turntable is rotated so that the monostatic radar has got the same aspect view at the target as the defined bistatic aspect angle and then the monostatic data are recorded.

In the following, to demonstrate the multiplicity of possibilities of parameter variations four different classification procedures will be introduced and exemplary classification results will be shown for a selection of different parameter configurations. Thereby it can be seen that any of the parameter configurations shown here leads to quite well classification results.

A. Correlation Classifier

The simple correlation classifier is based on the values of the correlation coefficients between a test-profile and each reference-profile. The Pearson correlation coefficient ρ is a measure of the linear dependence between two vectors x and y and is normalised between -1 and +1 with +1 meaning an entirely positive linear dependence, -1 meaning an entirely negative dependence and 0 meaning no linear dependence between x and y. It is given by

$$\rho = \frac{Cov(x,y)}{\sqrt{Var(x)} \cdot \sqrt{Var(y)}},$$

whereas in this application example the values of the covariance and the variances are estimated from the data. The test-profile is then considered as coming from that class

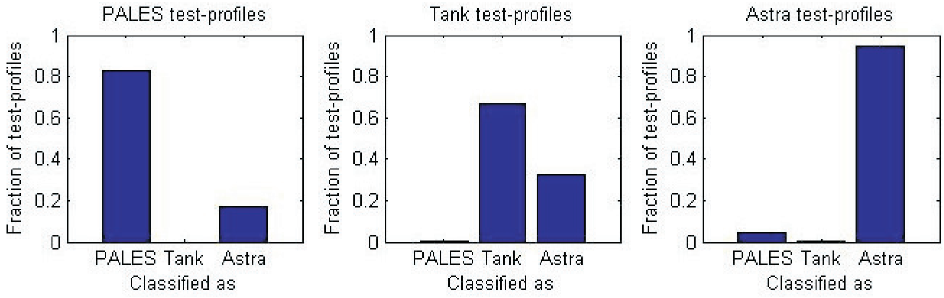

Fig. 7. Exemplary classification results for the correlation classifier.

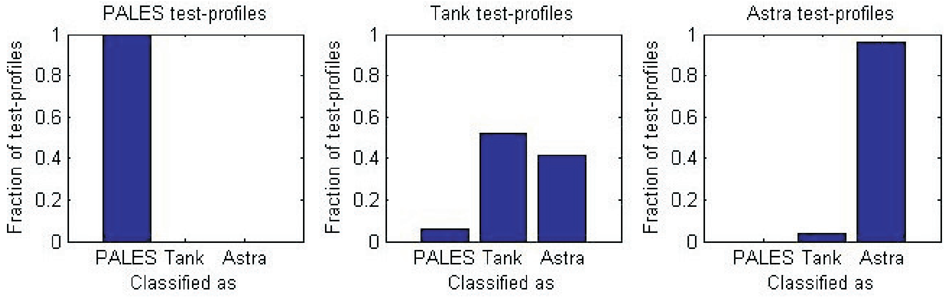

Fig. 8. Exemplary classification results for the NN classifier.

of vehicles, for which the correlation coefficient with the respective reference-profile is maximum.

In Fig. 7 classification results for the correlation classifier are displayed. The fraction of the test-profiles that has been assigned to the respective vehicle class is displayed. The test-profiles are single HRR-profiles, which have been recorded at a bistatic angle of 5°. The bistatic aspect angle has been defined as seen from the bistatic bisector. The reference-profile for each vehicle class has been built up by averaging the monostatic HRR-profiles of that class over the whole considered azimuth span of 10°, also without any previous smoothing.

B. NN ("Nearest Neighbour") Classifier

For the classical NN classification procedure the reference-profile with a length of n range cells is considered as a point in an n-dimensional hyperspace, whereas the amplitude of the k-th range cell determines the value of the k-th coordinate axis of the hyperspace $(k = 1, \ldots, n)$. The same applies to a test-profile, which must have the same number of range cells n. Then the Euclidean distance between these two points can be calculated. This is done for every reference-profile and then the test-profile is considered as belonging to that class of vehicles, for which this distance is minimum.

Fig. 8 shows exemplary classification results for the NN classifier. The test-profiles have been recorded at a bistatic angle of 5° and the bistatic aspect angle has been defined as seen from the bistatic receiver R5. They are not single HRR-profiles but average HRR-profiles generated by averaging HRR-profiles over a rotation of the turntable of 0.5°. Furthermore, the average HRR-profiles have been smoothed using a moving average with window size 5. Application of these smoothing techniques makes the test-profiles more stable and improves classification. The reference-profile for each vehicle class has been built up by averaging the monostatic HRR-profiles of that class over the whole considered azimuth span of 10° after the previously mentioned smoothing techniques have been applied to them. Additionally, test-profiles and reference-profiles have been normalised to have maximum amplitude 1.

C. Pop ("Presence-of-Peak") Classifier

The Pop classifier makes use of the fact that some peaks in HRR-profiles of a target always appear at similar locations over a moderate change in aspect angle. So only the locations of these peaks are used for classification and not their amplitudes because the locations are more robust than the amplitudes. Thus, for every class of vehicles the locations of robust peaks of their respective HRR-profiles are identified and stored in a database. Then a test-profile is classified like this: The ratio of the number of the locations of these peaks that are present in both the test-profile and one of the training-profiles in the database, to the number of locations of peaks of this training-profile is calculated. This is done for every class of vehicles separately. Then the test-profile is assessed as belonging to that class of vehicles, for which this ratio is maximum [7].

Fig. 9 shows classification results for the Pop classifier. The test-profiles have been recorded at a bistatic angle of 15° and the bistatic aspect angle has been defined as seen from the bistatic bisector. They are not single HRR-profiles but average HRR-profiles generated by averaging HRR-profiles over a rotation of the turntable of 1.5°. Furthermore, the average HRR-profiles have been smoothed using a moving average with window size 5. The same smoothing techniques have also been applied to the training-profiles.

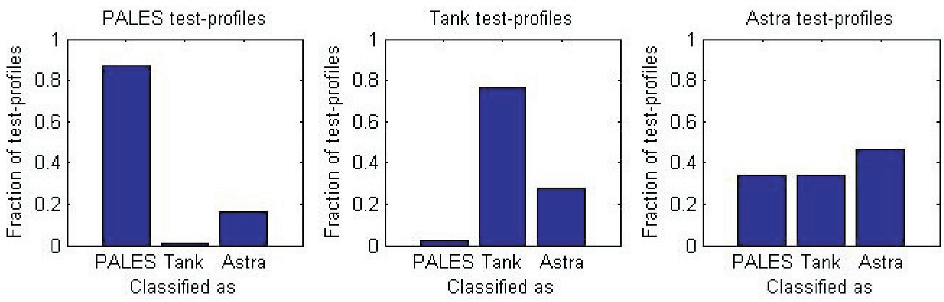

Fig. 9. Exemplary classification results for the Pop classifier.

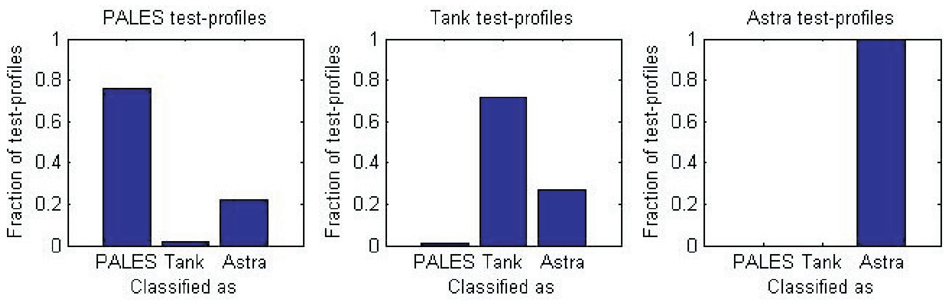

Fig. 10. Exemplary classification results for the CART classifier.

D. CART ("Classification And Regression Tree") Classifier

CARTs are a classification procedure with binary tree structure. The input variables for growing the CART are the single range cells of the HRR-profiles and their realizations are the amplitude values of the range cells. The tree growing procedure starts with a single node, which contains the HRR-profiles of all classes of vehicles. The final goal of the tree growing procedure is then to get a tree, of which each leaf node contains the HRR-profiles of only one class of vehicles. As a node splitting criterion the range cell is selected that best reduces the node impurity given by Gini's diversity index. Gini's diversity index is defined as $i(t) = \sum_{a \neq b} p(a|t)p(b|t)$, whereas t denotes the considered node and a and b denote the class membership. So, in general not the whole HRR-profile is used for classification but those range cells that best discriminate the data [8].

In Fig. 10 classification results for the CART classifier are displayed. The test-profiles have been recorded at a bistatic angle of 15° and the bistatic aspect angle has been defined as seen from the transmitter Tx. They are not single HRR-profiles but average HRR-profiles generated by averaging HRR-profiles over a rotation of the turntable of 0.5°. Furthermore, the average HRR-profiles have been smoothed using a moving average with window size 5. The same smoothing techniques have also been applied to the training-profiles. Additionally, test-profiles and training-profiles have been normalised to have maximum amplitude 1.

V. Conclusions and Future Work

It is important to mention again that the classification results shown above are just exemplary to demonstrate the possible parameter variations that were examined. In fact, classification experiments were carried out at any possible combination of bistatic angle, definition of bistatic aspect and averaging of HRR-profiles. Thereby it was found that all the possible parameter configurations more or less led to quite well classification results.

So for the small bistatic angles of 5° and 15° used here there was not really a difference in classification performance between the two possible bistatic angles. Sometimes the smaller bistatic angle and sometimes the bigger bistatic angle led to better classification results depending on the other parameters.

For instance, the classification performance was better when the HRR-profiles were averaged over a rotation of the turntable of 1.5° than when they were averaged over a rotation of the turntable of 0.5°. And with averaging the classification performance was always much better than without it, when only single HRR-profiles were used for classification.

Furthermore it was found that except for the CART classifier the best way in terms of classification performance to define the bistatic aspect was to define it as seen from the bistatic bisector. To define it as seen from the transmitter was the best way for the CART classifier and it was not much worse for the other classification procedures. The mean degradation in classification performance when all other parameters remained stable and only the bistatic aspect angle was changed from the bistatic bisector to the transmitter was approximately 4 percentage points except for the CART classifier. On the other hand, using the transmitter aspect as the bistatic aspect angle simplifies classification extraordinarily since a classifier has to be trained only once for any bistatic angle, and the question of how to incorporate the bistatic angle into the classification procedure can be circumvented. However, using the receiver aspect as the bistatic aspect angle was almost always inferior.

Most of the questions posed in Section 2 remained unanswered after the first experiments described in this paper and are to be examined in the near future. Especially the analysis of the scattering physics of a target in a bistatic radar configuration requires further investigation. A better understanding of these scattering physics would assist the construction of a bistatic reference database using only monostatic measurements even for larger bistatic angles.

Other interesting tasks that are planned to be examined are the classification of bistatic 2D-ISAR images and classification when multiple receivers are used. The latter includes the examination of data fusion techniques and the investigation of an ideal distribution of receivers.

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