FORWARD SCATTERING RADAR: CURRENT AND FUTURE APPLICATIONS

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ABSTRACT

Forward scattering radar (FSR) is a special mode of bistatic radar that can be used for target detection and classification. FSR offers a number of interesting features such as: relatively simple hardware; an enhanced target radar cross section (compared to traditional radar); a long coherent interval of the receiving signal; robustness to stealth technology and possible operation using non-cooperative transmitters. This paper discusses the FSR technology, the current and possible applications as well as the limitations of FSR. All claims in the paper are supported by the experimental result of the FSR feasibility study to the automatic ground target detection and classification. The paper introduces the radar system itself, this include the overall classification system and the extraction of features from the radar measurements.

Keywords: *forward scattering radar, ground target, target classification*

INTRODUCTION

In the Radar System, if the transmitter and receiver are collocated, this configuration is known as a monostatic radar system. In contrast, if the transmitter and receiver are separated by a distance comparable to that of the maximum range of the target, the system is known as a bistatic radar system. The monostatic and bistatic radar system configuration is illustrated in Figure 1(a) and (b) respectively.

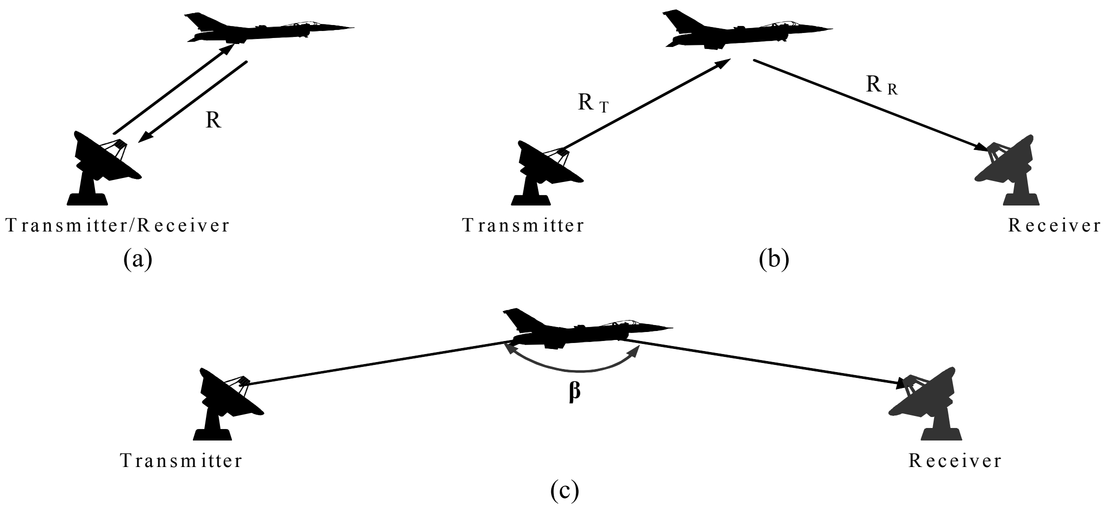


Figure 1: (a) Monostatic radar (b) Bistatic radar and (c) Forward scattering radar

Forward scattering radar (FSR) is a special type of bistatic radar, where the target is close to the transmitter-receiver baseline as shown in Figure 1(c). FSR presents a conservative class of systems that have a number of fundamental limitations, including the absence of range resolution and operation within narrow angles. On the other hand, FSR offers a number of peculiarities that make it a viable interest. Its' most attractive feature is the steep rise in the target radar cross section (RCS) compared to traditional monostatic radar [1–2], which improves the sensitivity of the radar system. The forward scattering RCS mainly depends on the target's physical cross section and the wavelength, and is independent of the target's surface shape as well as to any radar absorbing material (RAM) coating which reduces the target's RCS in traditional radar [3]. This feature makes FSR robust to stealth technology. In addition, by using inverse synthetic aperture algorithms in FSR, with their high cross range resolution, FSR can be used for target classification [4]. FSR also requires relatively simple hardware and has a long coherent interval of the received signal; this is the consequence of the loss in range resolution. Moreover, FSR receiver can utilise radiation from non-cooperative transmitter without revealing its location. In a hostile environment this is highly desirable as the receiver may be used covertly.

History of FSR

Before and during World War II, a so called 'forward scatter fence' was used for aircraft detection, and almost 200 of these fences were deployed by France, Japan and The Soviet Union [5]. These were bistatic radars, but their geometry was similar to the forward scatter configuration, where targets fly near the transmitter-receiver baseline. These radars used continuous wave (CW) transmitters, so the receiver detected a beat frequency produced between the direct signal from the transmitter and the Doppler frequency shift scattered by the moving target. During that time, these forward scatter fences were found to be of very limited use for air defence. Since the coverage area is very narrow, only targets that penetrated a single given fence could be detected. If the target rapidly flew out of that fence it could not be located and tracked. Only when adjacent fences were deployed an approximate position and velocity could be estimated. This problem causes the complex nature of the system. Consequently, most of the early forward scatter fences were eventually replaced by monostatic radars which have better spatial coverage area and location accuracy.

Currently, electronic fences or microwave fences are widely used in security applications to protect large territories. As far as we concern, only one set of research is currently under way for the FSR development for air defence systems that is in Russia [6 – 8].

FSR Technology

In bistatic radar, one of the factors affecting the electromagnetic (EM) field strength and pattern at the receiver is the angle that the target makes to the transmitter and receiver, this angle is called the bistatic angle, β. When the bistatic angle is equal or near 180° ($\beta \approx 180°$), the radar system is referred to as FSR system as shown in Figure 1(c). At forward scattering, the presence of a target will partly block the signal wavefront from the transmitter. This blocking yields a hole in the wavefront, known as the target shadow. This shadow is actually an EM field being scattered by the target. This follows the EM field theory that is [9], when there is an absolutely black body that is placed in the path of wave propagation and the dimensions of this body are large compared with the wavelength, then a scattered field exists behind the body (a 'shadow' field)'. This field is a result of primary field disturbances. The scattered field could be represented as the shadow lobe, and this lobe pattern follows the antenna pattern of a uniformly illuminated flat antenna in the shape of the shadow with negative illumination (180°) relative to the primary field [10]. The shadow field polarisation is the same as that of the incident wave. Since the pattern of the shadow depends on the target's silhouette, it does not depend on the target's surface shape. This characteristic shows the independence of the forward scatter RCS to the RAM coating which reduces the scattered field generated by surface currents on the target, and hence the traditional monostatic RCS [9].

Another important aspect of forward scattering is that, the target's coherence time is rather high and specified by the stability of the transmitter at the baseline. This is a direct consequence of the range resolution losses. Complex targets in FSR have reflections similar to those from the point targets. On the other hand, because of the absence of range resolution, signals in FSR do not experience fluctuation due to the target's natural swinging.

The Current Status of FSR

To the best of the author's knowledge, this research is the only systematic study of this problem in the world. The study is to show the feasibility of FSR to ground target classification. Taking into account that the development of a full-scale electrodynamic model of complex 3-D targets at a heterogeneous background is not feasible, an experimental approach was taken. Being a feasibility study, this research is not targeting the comprehensive radar system analysis; but forms a foundation to develop a complete radar system in the future. We have developed an experimental 890MHz ground-based FSR for targets automatic classification using their Doppler signatures. The experiment was done on a public road transport. The sensor is placed about 1 metre above the ground with the transmitting and the receiving antennas facing each other on different sides of the road. The transmitted microwave field is diffracted by the moving vehicle as it passes the forward scattering region. This field contains Doppler frequency components due to the vehicle motion. The Doppler spectrum of the diffracted field is used to create the vehicle's signature, which is the input to the classification algorithm.

The proposed system is low cost, simple, easy to install and uses only CW or narrowband signals at low frequency, making it robust to any weather conditions. In this section the FSR system is described, the methodology on getting the FSR system to be viable is discussed and all the relevant results are presented.

FS Sensor

Figure 2 illustrates the simple FSR radar block diagram and the system topology used for vehicle classification. It comprises two major parts: the hardware (the radar itself) and the software (classification algorithm). The transmitter is a continuous wave (CW) generator connected to low gain or omnidirectional antenna, while the receiver includes a non-linear component to select Doppler frequency, which after low-pass filtering, gaining and A/D conversion are ready for signal processing. The software includes the basic FFT, target speed estimation algorithm, feature extraction using the PCA method, and the classification algorithm. The waveform at the receiver input contains the signal with Doppler frequency diffracted from the moving vehicle as well as a direct signal from the transmitter. When these signals pass through the non-linear device (diode), they introduce Doppler frequency components, which are then used in further signal processing. These signals are referred to as the 'vehicle signature'.

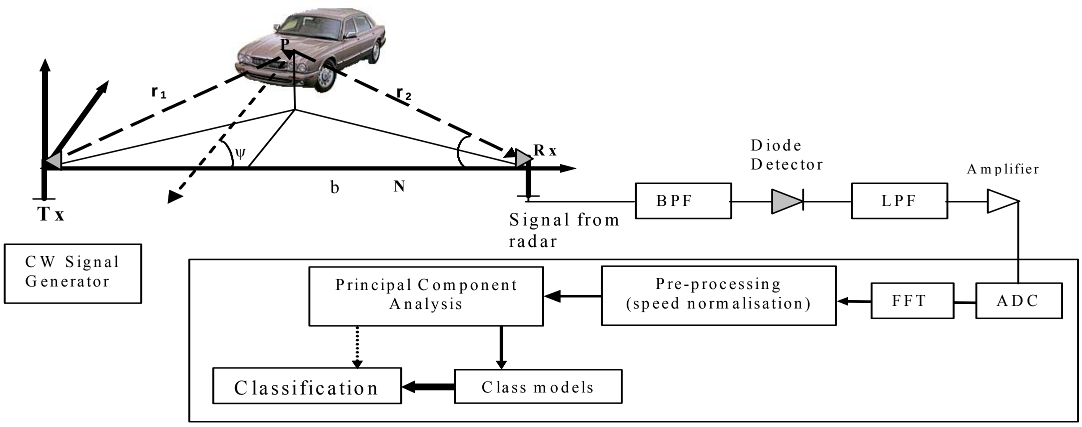


Figure 2: FSR block diagram for vehicle classification

Vehicle Data Collection

An experiment to collect data using real vehicles was carried out on a public road using the setup shown in Figure 3. During this experiment, signals from a random stream of vehicles as well as a number of test vehicles were collected and recorded. Figure 4 shows a sample of the captured waveform, both in time and frequency domains, when a vehicle passed between the transmitter and receiver.

In addition to the recording vehicle signatures, the speed of each vehicle was recorded in this set of experiments using a video camera that captured the scene of the experiment as shown in the photo of Figure 3. As detailed in the following section, the knowledge of the vehicle's speed is an important part of data processing in order that each vehicle plot could be scaled to a reference speed prior to classification. In order to estimate speed, two posts, separated by 16m, were placed within the scene of the experiment (the two white lines in the photo of Figure 3) to provide a reference distance. By playing back the recorded video, the speed of a particular vehicle can be evaluated by measuring the time taken for a vehicle to travel between the two posts.

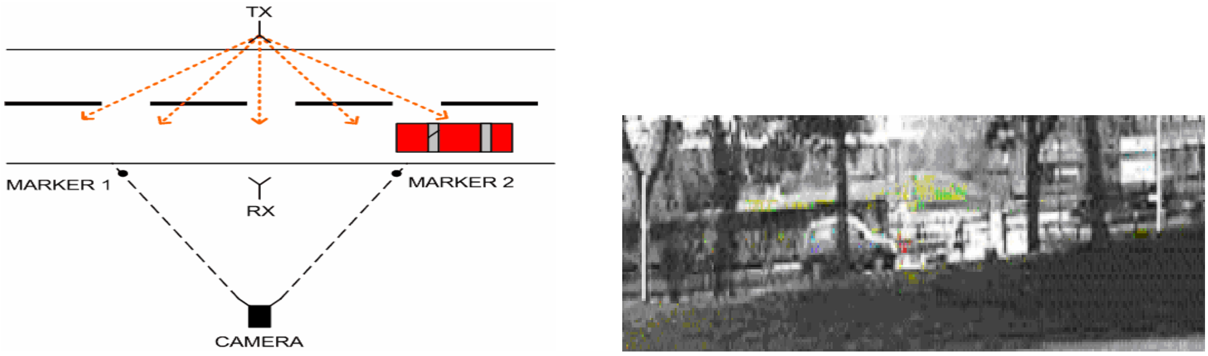


Figure 3: Experimental setup block diagram and a typical video from the test day.

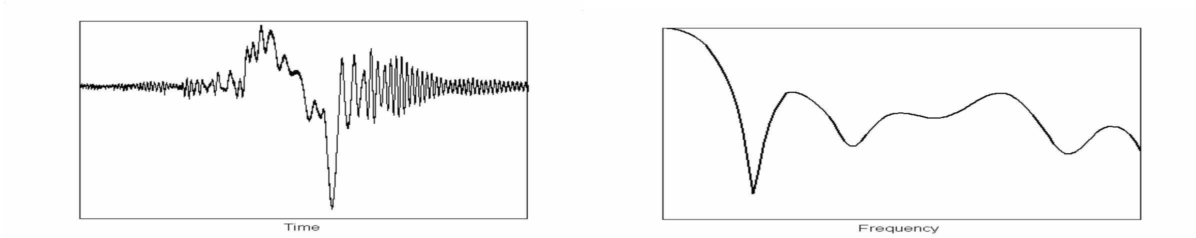


Figure 4: Sample vehicle signature in both the time and frequency domains.

THE CLASSIFICATION SYSTEM

Feature Extraction Using the Principle Component Analysis

Let us denote by **o** the spectral feature vector as obtained from the pre-processing block (see the block-diagram on Figure 2). Such feature vector is of a high-dimension and the features are highly correlated. We employed the Principal Component Analysis (PCA) as a means of reducing the dimensionality of the spectral feature vector by exploiting the correlation between the features. The PCA technique has often been used in various data classification problems [11 – 12]. The PCA projects high-dimensional data onto a lower-dimensional space (called principal component space) by using the projection that best represents the data in a least-squares sense [13]. The principal components are arranged in such order that the amount of variance of the data explained by each principal component is non-increasing. Often only the first few principal components are necessary to represent the information contained within the data.
The PCA technique performs a linear transformation of a given spectral feature vector **o** into the principal component space, resulting a new feature vector **O**, i.e.

$$O = W \cdot (o - m)^T \tag{1}$$

where **m** is the mean vector of the training data and **W** is the transformation matrix, both obtained from the training data.

Obtaining PCA parameters from the training data

Let us assume a training set of feature vectors $\{o_c^i\}$, where o_c^i is the ith feature vector of dimension *N* from the category c. The PCA decomposes the covariance matrix **S** calculated from the entire feature set into

$$S = ULU^T \tag{2}$$

where **L** is a diagonal *NxN* matrix containing the eigenvalues sorted in a non-increasing order of magnitude and **U** is a *NxN* matrix containing the eigenvectors.

The transformation matrix **W** is formed by the eigenvectors corresponding to the first *M* highest eigenvalues, i.e. $W = [u_1; u_2; \ldots; u_M]$. The value of *M* is usually low and can be decided empirically based on the amount of variance explained by the eigenvalues.

Classification

In the training phase, the PCA transforms each training feature vector o_c^i into the space defined by *M* principal components. Each transformed training feature vector O_c^i is associated with a label (vehicle category or model in our case). These form the models of each class and are used during the classification of an unknown vehicle. In the classification phase, the system captures a signal corresponding to an unknown vehicle passing through the radar system. This signal is passed to the pre-processing block and the spectral feature vector, denoted $\mathbf{o_u}$, is obtained. The feature vector $\mathbf{o_u}$ is then transformed into the PCA-space by using Equation (1), resulting a new feature vector $\mathbf{O_u}$.

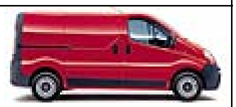
The final step of the classification is to use a classification rule decide tothe class (e.g. vehicle-category) of the unknown vehicle based on the feature vector O_u. Various classification rules can be used, for instance, one can (based on the training data) model the probability density function corresponding to each class and then apply a Bayesian decision rule, or use a neural-network classifier. Due to the limited amount of training data, for this work we employed a simple classification rule; namely the k-nearest neighbour classifier.

EXPERIMENTAL EVALUATION AND RESULTS

Vehicle-Category Classification

A test system for the experimentation has been developed to prove the concept. During experimentation, 850 car signatures were obtained from the free flow road and stored in the database. The goal is to automatically classify these cars into one of three conditional vehicle-categories; namely, Small car, Medium car and Large car. Typical examples of models from each category were used as training data (reference signature) and presented in Table 1.

Table 1: Vehicle-categories with the corresponding car-models used in the training phase of the classification system

Vehicle-category	Example of car-models in the training data	N_A	**Representative car model**
Small	Honda Civic, Peugeot 206, Ford Ka, BMW Mini	95	
Medium	VW Golf, Peugeot 406, Vauxhall Astra , Ford Focus, Mercedes E-class, VW Passat, BMW	192	
Large	Renault Traffic, Vauxhall Combo	140	

N_A = Number of vehicles for each category in the training data.

Figure 5 shows a plot of all the training data in the principal component space (for clarity reasons we only show a 2D plot). It can be seen that examples of each vehicle-category are located in different parts of the PCA-space with little overlap between the categories. In this experiment, we used the first three principal components for the classification process, which described 91% of the variance of the training data. The k-nearest neighbour classifier with k=3 was used.

In total, 427 signatures for the test data, consisting of different types of models, were taken from the main database. These types of models signatures are not included in the training set. The testing data can be visually classified into the vehicle categories according to the image from the video camera. This is then compared with the category label acquired from the automatic classification system. The category classification results are presented in Table 2. The results show that very good performance of the system can be obtained with a limited amount of data for both testing and training. From the results we can see that classification was correct by 75% for Small car, 89% for Medium car and 71% for Large car. It is difficult to obtain clear categorisation of vehicles and therefore the main errors occurred between neighbouring categories. For example, 22% of Small car were classified as Medium car, and 25% of Large car were classified as a Medium car whereas there was only 2 – 4% error between Small and Large car.

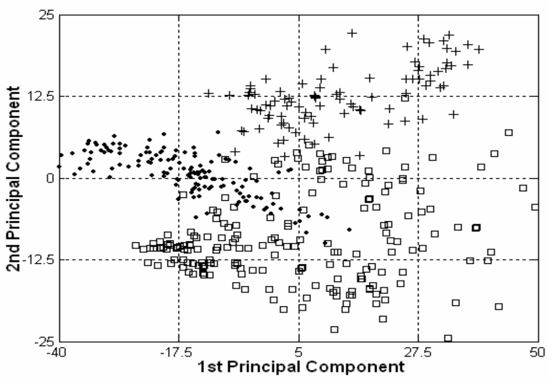


Figure 5: The location of training data of each vehicle-category in the PCA-space.
Notation: Small (+), Medium (□), Large (●)

Table 2: Vehicle-category classification results

Category classified from video image	N_V	Automatically classified as [%]		
		Small	**Medium**	**Large**
Small	234	**75**	22	3
Medium	134	9	**89**	2
Large	55	4	25	**71**

N_V = Number of vehicles for each category in the test data.

Vehicle-Model Recognition

This section presents the results obtained for recognising a specific model from a collection of vehicle-models. In the database, we have four vehicle models; namely, Honda Civic (70 examples), Vauxhall Astra (132 examples), Vauxhall Combo (81 examples) and Renault Traffic (60 examples). Fifty data examples from each model were used for training and the rest were used for testing. The classification method and the number of principal components used are the same as in Section 4.4.1. Table 3 presents the experimental results. A very good match can be seen; with 100% correctly recognised for Honda Civic, 97% for Vauxhall Astra, 91% for Vauxhall Combo and 80% for Renault Traffic.

Table 3: Vehicle-model recognition results

Vehicle-models	Automatically recognised as [%]			
	Honda Civic	Vauxhall Astra	Vauxhall Combo	Renault Traffic
Honda Civic	**100**	-	-	-
Vauxhall Astra	1	**97**	2	-
Vauxhall Combo	3	6	**91**	**-**
Renault Traffic	-	-	20	**80**

CONCLUSION AND FUTURE APPLICATION

This study has confirmed the high sensitivity for target detection and classification in FSR. Based on the presented result, it is proved that FSR system has a huge potential to be used as an alternative system for ground target detection and classification. The benefit of using FSR for ground target classification is that it could be useful in many applications where currently microwave fences are used.

In recent years there has been a marked increase in the use of micro-sensors (MS) technology. MS comprise of a variety of sensors connected in a network. An individual sensor is simple, miniature and low-cost. It can detect an intruder which crosses the receiver-transmitter line. Technically, the transmitter is a low battery powered CW generator whose signal is received by a receiver over the line of sight distance. When a landscape is sophisticated these sensors can form a linear net, where each transceiver is used as the communication net node. This MS net could have an arbitrary configuration, depending on applications, to prevent an intrusion in a particular area. The transceiver can be deployed to their position by ‘spreading’ from aircrafts (including unmanned), or purposely placed at a known position, etc. Having a GPS receiver on the MS transceiver board, the node position is known. The data received from this net carries a lots of useful information regarding protecting an area. Using the effect of Shadow Synthetic Aperture that exists in forward scattering (FS) radar, a Forward Scattering Micro Sensors (FS MS) could be developed. However, the current status of this system study is not enough for vulgar results extrapolation into ground applications. Potentially the proposed FS MS net can complement or replace optic systems, taking into account that: it operates at a low RF band which is absolutely robust to weather and other external conditions; transparent for foliage, grass and similar natural ‘maskirovka’; for the target classifications narrowband data is used (signature vs image in optical systems), this is important if the signature needs to be transferred over a low data rate communication channels; transceivers are simple and do not require orientation when deployed; it can be developed and installed as a disposable stuff. Applications of these systems for a ground force operation are a fundamentally new and promising topic, which comprises both a new theoretical study and technical implementations.

REFERENCES

[1] Boyle R.J. (1994) Comparison of Mononstatic and Bistatic Bearing Estimation Performance for Low RCS Targets. IEEE Transactions on Aerospace and Electronic System, **30**(3): 962-968.
[2] Glaser J.I (1985) Bistatic RCS of Complex Objects Near Forward Scatter. IEEE Transactions on Aerospace and Electronic System, AES **21**(1): 70-78.
[3] Hiatt R.E., Siegel K.M., Weil H. (1960) Forward Scattering of Coated Objects Illuminated by Short Wavelength Radar. Proceeding IRE, pp. 10-11.
[4] Chapurskiy V.V and Sablin V.N. (2000) SISAR: Shadow Inverse Synthetic Aperture Radiolocation. International Radar Conference, The Record of the IEEE 2000 International, pp. 322-328.
[5] Willis N. J. (1995) Bistatic Radar. Technology Service Corporation.
[6] Blyakhman A.B. (1998) Multistatic Forward Scattering Radar. PIERS Workshop on Advances in Radar methods, Italy, Baveno, pp.107-113.
[7] Blyakhman A.B, Ryndyk A.G. and Sidorov S.B (2000) Forward Scattering Radar Moving Object Coordinate Measurement. Radar Conference. The Record of the IEEE 2000 International, pp. 678-682.
[8] Blyakhman A.B and Runova I.A. (1999) Forward Scattering Radiolocation Bistatic RCS and Target Detection. Radar Conference, 1999. The Record of the 1999 IEEE, pp. 203-208.
[9] Chernyak V. (1998) Fundamentals of Multisite Radar Systems. Gordon and Breach Science Publishers.
[10] Barton D.K. (1988) Modern Radar System Analysis. Artech House.
[11] Lavine B.K. (2000) Clustering and Classification of Analytical Data. Encyclopedia of Analytical Chemistry: Instrumentation and Applications, John Wiley & Sons Ltd., Chichester, pp. 9689-9710.
[12] Köküer M., Murtagh F., McMillan N.D., Riedel S., O'Rourke B., Beverly K., Augousti A.T. and Mason J.. (2003) A wavelet, Fourier, and PCA Data Analysis Pipeline: application to distinguishing mixtures of liquids. Journal of Chemical Information and Computer Science, **43**: 587-594.
[13] Duda R.O., Hart P.E. and Stork D.G. (2000) Pattern Classification. John Wiley & Sons.

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