Speed Recognition Based PCA on Ground Vehicle in Passive Forward Scattering Radar

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***Abstract*— The merging of noise reduction and reshaped of the signal in time domain is headed to newfangled clustering methods. After a deep investigation on pre-processing the detection of ground vehicle using passive forward scattering radar (PFSR), principal component analysis (PCA) could be used as spectral signature for target's speed recognition. The clustering-based PCA able to distinguish the target's rapidity from the passive forward scattering radar receiver. A small five door hatchback vehicle is used for detection as ground vehicle with several speed and various distance from the passive forward scattering radar receiver. The distance give impact to the clustering-based PCA which is closer vehicle to the passive forward scattering radar offers finer variance of training data in speed recognition.**

***Index Terms*— PSFR; PCA; Forward scatter; Speed recognition.**

I. INTRODUCTION

Passive forward scattering radar (PFSR) system provides a new, emerging area of research which effectively operates against stealth targets. According to standard passive radar systems, there is nonexistent customized transmitter. As an alternative, the receiver maneuvers non-observance sources of illumination in the atmosphere and then compares the time difference of the signal arrived at receiver between the direct signal from the illuminator and the echo signal from the target [1]. As a result from the target detection permits the position and pace of the moving target to be estimated and complex pre-processing is used to suppress the high amplitude of direct signal. Instead, forward scatter (FS) mode is improved to conventional passive radar system without any complicated pre-processing signal. Thus the clustering-based principal component analysis (PCA) capable to make the passive forward scattering radar (PFSR) system more effective and valuable [2].

The principal component analysis is a numerical method which uses an orthogonal alteration in examining the maximum variance of data trend and is often accustomed to shrinkage the data dimension [3]. While signal processing, it should be significantly cautious when removing the noise from the signal because it may contained the specifics of maintaining significant signal. As a consequence, PCA is a simplifier in minimizing dataset to the marginal dimension which is highly practical in signal processing and recognizing the pattern of the signal. Additionally, PCA is a fruitful method to highlight the similarities and differences of identifying patterns in data and express the data.

The usefulness of PCA is depend on the principal components which able to thinly the extract signal. On top of that, the sporadically might be realized by clustering modus which consists of finding the alike squares in an unsubstantiated mode using a flexible separation to the signal converted into fragmented regions which only needs fewer computation. Furthermore, through matching the nearness of the candidate square with the center of dissimilar cluster to establish the threshold in the clustering modus, is generating the clustering method with greater accomplishment in finding appropriate squares. By adopting the K-means algorithm [4], it could be further minimalism and quickness. Besides, supplementary of the Euclidean distance to the K-means algorithm also could quantify the homogeneity in feature space which give greater and modest unconventional to the feature extraction that had been examined in synthetic aperture radar (SAR) images [5, 6].

The merging process of de-noising, filtering and clustering-based PCA on the detection of ground vehicle in passive forward scattering radar signal processing is a new frontier to recognize the speed of ground vehicle with several distance from radar receiver which is the main aim of this research paper.

II. SPEED RECOGNITION BASED PCA

A. Ground Vehicle Detection

A ground vehicle had been maneuvered for data collection in target detection using passive forward scattering radar system. In Figure 1, it shows the geometry of passive forward scattering radar system using illuminator base station as a co-located transmitter. Subsequently, the ground vehicle is moving with several speed in between the passive forward scattering radar and the illuminator base station for target detection. In addition, the real dimension of small five door hatchback vehicle is 3395 mm (length), 1405 mm (width) and 1415 mm (height). The speed of the ground vehicle are divided into four speeds which are 5, 10, 20 and 30 in the unit of km/h. The distance of the ground vehicle to the passive forward scattering radar are separated into three ranges which are 5 meter, 10 meter and 20 meter. The data collection of this ground vehicle detection using passive forward scattering radar system took around 40 samples for every each speed and distance which means total of data collection is 480 samples. Following, this samples is used for speed recognition using principal component analysis.

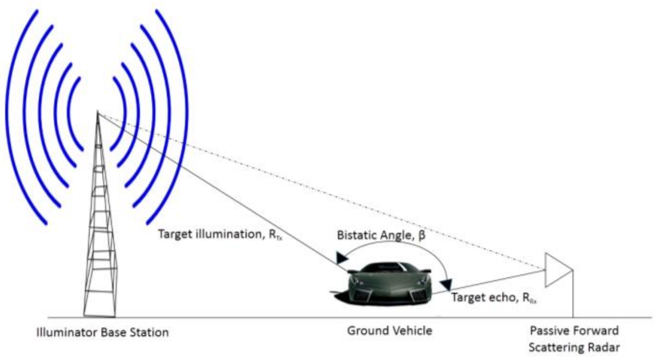

Figure 1: Passive forward scattering radar system

B. Evaluation on Speed Clusterization

The idea of the clustering the speed of detection ground vehicle using passive forward scatter radar is illustrated in Figure 2. Firstly, the original input signal in time domain is denoised using wavelet technique which proved to be more efficient and uncomplicated in converting the time domain into smooth signal after removal the noise. Following with fast Fourier transform (FFT) [7] which is transformed the denoised signal into the frequency domain signal. Afterward is power spectrum density transformation using Welch's method which is used to evaluate the signal in terms of power at variation frequencies based on the concept using periodogram [8]. The power spectrum density is normalised before it used for data matrix in principle component analysis (PCA) where PCA is used for spectral signature description in an effective method. Lastly, the signature description will be input for clustering scheme as illustrated in Figure 2.

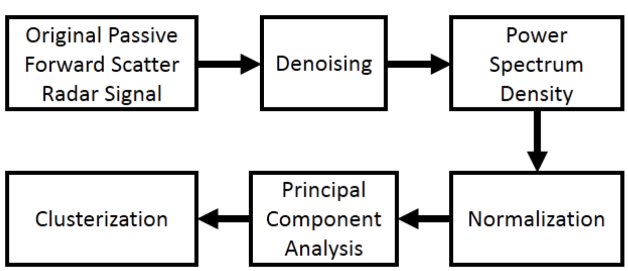

Figure 2: Speed clusterization block diagram by using original signal from passive forward scattering radar detection

C. Clustering Scheme

The clusterization method have two stages which are training and recognition. The training stage have a training set of feature vectors which correlate with categorization of class. Initially the PCA transformation with matrix W is figured out for the principal of the training data set. Next, for every training feature vector is going the transformation into the PCA dimension as in equation (1). As we can comprehend the formula, an assign of transformed feature vectors {Oc}i arrangements a models for every each of the category, c, in which it is practical for the clusterization of an unidentified baseline target.

The recognition stage is about an encapsulation signal which coincide with an unidentified baseline target passing in between the passive radar receiver and source of illuminator. Then, the encapsulation signal is used to acquire the speed normalised spectral feature vector symbolized as Ou and next transformed it into the PCA dimension. Finally, clusterization resolve the unidentified class of baseline target established by the feature vector Ou and make a model for every each of the class. The K-nearest neighbour (3 neighbours) with Euclidean distance was used in this research paper.

D. Principal Component Analysis

Principle components analysis (PCA) is utilized to define the spectral signature in a better operative way where the signature is used to be the input of clusterization. As remarkable the spectral feature vector which attained from the earlier stage of processing is not suitable for the circumstances of clusterization for the reason that it contains large dimension which may affect the features correlation. Consequently, PCA could contribute in minimizing the large dimension of the spectral feature vector inherently clustering the data by exploiting the correlation between the features. PCA is also so called the principal component space which is estimate the finest data using a least square method [9]. Subsequently, PCA could carry out a linear transformation from the spectral feature vector, o into the principal component space which produces the unique feature vector O as in equation (1):

$$O = Z\left(o - x\right)^{T} \tag{1}$$

where Z is a transformation matrix and x is mean feature vector of the training data. The calculated of covariance matrix from the whole training feature assign could be indicated as Y where PCA deteriorations the covariance matrix, S into simple mathematical expression, $Y = ULU^T$. L contains eigen values assembled in a non-increasing order of magnitude expressed in a diagonal NxN matrix and U contains eigen vectors expressed in a NxN matrix. Therefore, Z is formulated by the eigen vectors correlating to the first X highest eigen values, Z = [u1; u2; . . . ; uX].

III. Results and Discussion

Table 1 shows experimental results of variance explained on training data. In this experiment, 160 samples is used from three types of target's distance from the passive forward scattering radar receiver (5, 10 and 20 meter). Four types of target's speed of the ground vehicle to be recognized by clustering-based PCA (5, 10, 20 and 30 km/h). For every each type of target's distance with same speed used 40 samples. Overall 480 samples is used for the training data in the principal component analysis. Finally, the nearest distance of ground vehicle to the PFSR contributes a finer variance explained, such as described 75% of the variance of the training data for 5 meter of distance as shown in Table 1. However, for 10 meter and 20 meter have variance explained 72% and 68% respectively. As we know that PCA is a components which is not so robust in the meaning of PCA might remove the outliers and undesirable data which affect the results.

Table 1
Experimental results of variance training in speed recognition

Distance (meter)	Variance Explained (%)
5	75
10	72
20	68

A. PCA for Various Speed of Ground Vehicle

Figure 3 shows the principal component space for ground vehicle with various speed and distance of 5 meter away from the PFSR receiver. It can be seen that target's speed of 5 km/h in shape of magenta square have its own section in between -90 until -10 of principal component 1 (PC1) and -35 until 20 of principal component 2 (PC2). Subsequently, adjacent batch after 5 km/h is 10 km/h of target's speed which only have 5 km/h difference as the predictable result. The blue diamond batch (10 km/h) have a minor overlap with 5 km/h batch and have its own zone, -50 until 20 of PC1 and -5 until 23 of PC2. Then, neighboring batch is 20 km/h with red triangle. It is in range 0 to 50 of PC1 and -35 to 0 of PC2. Finally, target's speed of 30 km/h (black dot) have isolation area localized on the upper-right within the range 30 until 60 and 0 until 30, of PC1 and PC2, representatively. These expected results due to Doppler shift from the target's speed. It is indicates that if the target speed increased, the target's signature is compacted and if the target speed decreased, the target's signature is prolonged.

Figure 4 shows PCA for 10 meter distance between the target's baseline and PFSR receiver. It can be seen that target with speed of 30 km/h (black dot) had cross the threshold of 10 km/h batch (blue diamond). The 30 km/h in the range of -20 to 50 (PC1) and 0 to 40 (PC2). Following with 10 km/h in the range of -70 to 20 (PC1) and -12 to 15 (PC2). Even the target speed of 10 km/h have partially intersect with 5 km/h (magenta square) batch of speed, where the 5 km/h is localized right side of the graph area in the range 0 to 20 of PC1 and -32 to 15 of PC2. However, the 20 km/h batch (red triangle) still have its own zone in the range 0 to 60 and -30 to -5, of PC1 and PC2, respectively.

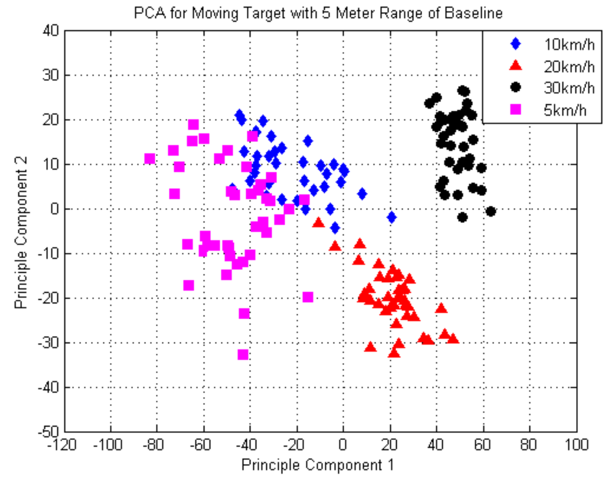

Figure 3: Location of training data for ground vehicle with distance of 5 meter in the PCA space

Figure 5 shows PCA for the ground vehicle moving in front of PFSR receiver with 20 meter distance away. It seems that almost all batch of the target's speed are overlap each other. The speed of 5 km/h in the range of -50 to 20 (PC1) and -40 to 25 (PC2). Next, 10 km/h in the range of -60 to 40 (PC1) and 0 to 35 (PC2). For 20 km/h, it is in the range of 10 to 50 and 0 to 30, for PC1 and PC2, respectively. Finally, target speed of 30 km/h within the range 0 until 80 of PC1 and -50 until 10 of PC2. This spread due to the distance between target and PFSR receiver, the nearest of the target to the PFSR receiver, the clearest of target's signature in time domain, and the other way round.

The results of PCA space proved that the speed of the same shape and size of the ground vehicle could be determined if the distance of the target to the PFSR receiver is known. Clearly, this PCA analysis is one of the method that used to highlight the similarities and differences of identifying patterns in signal processing and express the data signature.

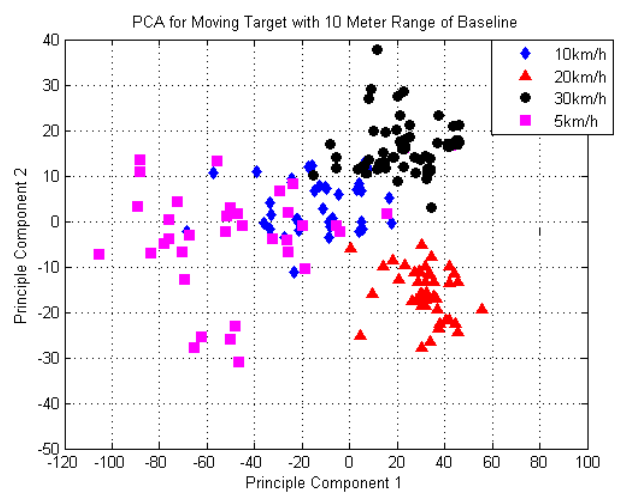

Figure 4: Location of training data for ground vehicle with distance of 10 meter in the PCA space

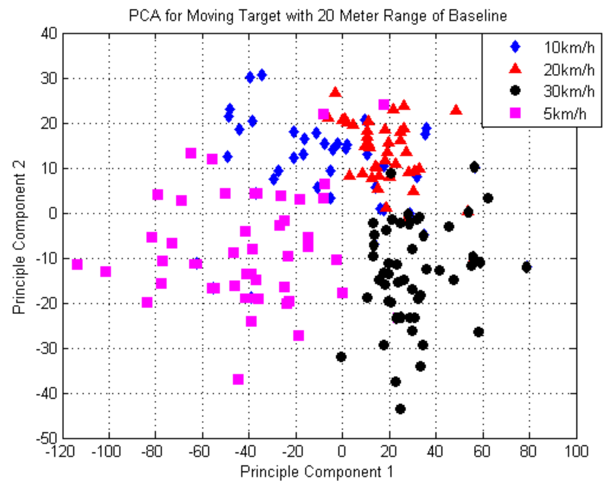

Figure 5: Location of training data for ground vehicle with distance of 20 meter in the PCA space

B. PCA Variance

In statistics, explained variation measures the proportion of variation a specified dataset with calculated model. Frequently, variation is enumerated as variance. Therefore the definite term variance explained is used. Figure 6 shows the PCA variance explained of training data with distance of the target to PFSR receiver is 5 meter range of baseline in the PCA space. It describes 75% of the PCA variance of the training data using the first principal components. Following, Figure 7 shows 72% variance explained for 10 meter range of baseline and Figure8 shows 68% variance explained for 20 meter range of baseline. PCA variance for 5 meter range of baseline is highest among the variation of distance between the ground vehicle and the PFSR receiver where it is competently used first one principal component.

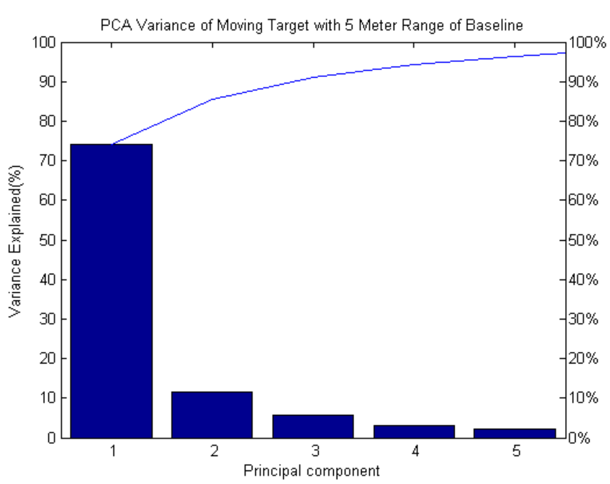

Figure 6: Variance explained of training data for ground vehicle with distance of 5 meter in the PCA space.

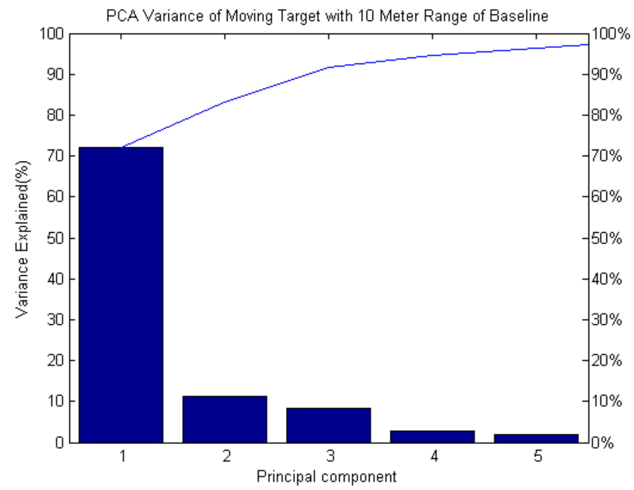

Figure 7: Variance explained of training data for ground vehicle with distance of 10 meter in the PCA space

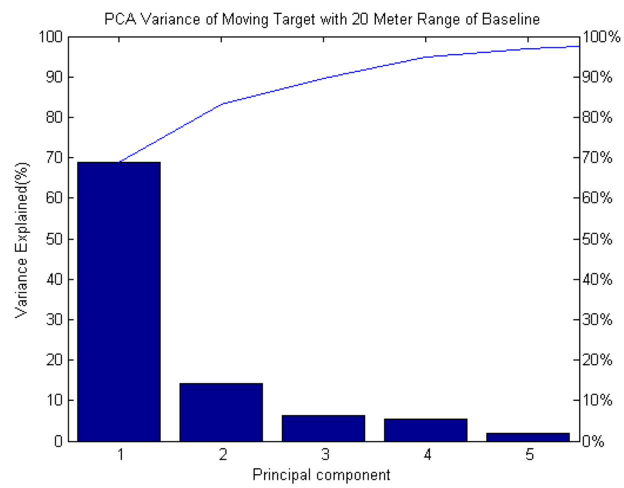

Figure 8: Variance explained of training data for ground vehicle with distance of 20 meter in the PCA space.

IV. CONCLUSION

Passive forward scattering radar in speed recognition of ground vehicle offers an advanced and essential area of exploration which effectively operates in contradiction of stealth targets and low silhouette targets overpass the transmitter-receiver region or so-called baseline. Results from the experimental proved that the speed recognition of ground vehicle detection using PFSR could be clustered using principal component analysis. The distance of the ground vehicle (target) give impact to the clustering-based PCA which closer distance offers finer variance of training data. In addition, the target's speed features by using the targets power spectrum density have shown good clusterization performance. Although the significant results achieved, additional pre-processing signal is needed for further investigation in order to strengthen the PFSR for target's speed recognition.

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