*ICIC Express Letters* ICIC International ©2018 ISSN 1881-803X
Volume **12**, Number **3**, March **2018** pp. **191–198**

# 3D TARGET DETECTION AND CLASSIFICATION BASED ON RADAR SENSOR FUSION

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Received September 2017; accepted November 2017

Abstract. *The importance of enhancing intelligent system performances has gained more attention. In this paper, a monitoring system based on Radar Sensor Fusion (RSF) has been proposed. Since such networks suffer from the energy consumption problem, the modified HEED routing protocol has suitably been considered to prolong the network lifetime. As radar sensor measurements mixed with noise at the base station, the linear Kalman filter (LKF) was applied to mitigating each sensor measurement noise. In addition, two targets – ground vehicle and drone were detected and classified. These tasks were achieved via trilateration/multilateration algorithm and non-linear least square, and fuzzy logic respectively. Simulation results showed that the monitoring system has successfully detected 3D target position and classified the target.*
**Keywords:** Kalman filter, Radar sensor, Sensor fusion, Trilateration/multilateration algorithm, Fuzzy logic, HEED routing protocol, Non-linear least square

1. **Introduction.** Wireless Sensor Networks (WSN) have been utilized in various fields in order to monitor and measure the environment conditions and physical phenomena [1-4]. WSNs consist of distributed sensor nodes. These nodes deploy randomly or manually collect and send data to a base station where the final process is to analyze it [5,6]. Since such networks have limitations in their resources (energy, bandwidth, etc.), there has been numerous research to mitigate the impact of these constraints. For example, clustering and enhancing routing protocols can prolong the lifetime of a network. Many protocols have been utilized and shown that the lifetime has been increased [6,7]. Consequently, that has become suitable to accomplish a number of applications such as home control, building automation, industrial automation, medical applications, highway monitoring, military applications, civil and environmental engineering applications, and habitat monitoring [8]. In military or civil surveillance application, WSNs are able to provide the same performance as single high cost network [8]. Thus, localizing objects and monitoring a field can be implemented.

In this paper, we aim to establish a monitoring system such as in [1] that is able to detect precisely a fixed target position and classify its kind in an outdoor field based on radar sensors. As [9] compared the output of distinct algorithms to detect the target position in 3 dimensions and [10] managed locating the target in 2 dimensions, we combine two algorithms (the T/M algorithm and the non-linear least square) to determine the exact target position in a less computation time.

The organization of this paper is divided into five sections. Section 1 introduces generally the WSN and its applications. In Section 2, sensor fusion and type are presented. For Section 3, the proposed monitoring system is fully demonstrated. In addition, Section 4 shows and discusses the results. Finally, Section 5 concludes this paper.

## 2. Sensor Fusion and Type.

**2.1. Sensor fusion.** Although [12] suggests using the terminology: information fusion instead of other terms such as data fusion, sensor fusion or multisensory data fusion, sensor fusion can be considered a term when combining data from the same sensor; that is called in this case direct fusion systems [12]. As a result, the sensor fusion aids to decrease the system complexity [11]. In WSNs, a method of gathering data is classified into homogenous, heterogeneous, hybrid networks [11]. Heterogeneous network contains sinks (fixed or mobile), normal sensor nodes, and sophisticated sensor nodes with advanced embedded system [11]. The hybrid network is a mixture of the previous kind. In this network, the long lifetime can be enhanced in comparison to the networks mentioned previously [11].

According to the type of sensor configuration, sensor fusion can be classified into three kinds: complementary, competitive, and cooperative. Complementary configurations require that each sensor measurement should totally be independent from other sensor measurements. Thus, combining data is easy for obtaining a whole image of the observed phenomena [12]. In competitive configurations, each sensor has independent measurements for the similar observed phenomena. For cooperative configurations, they combine measurements from independent sensors into data so that they achieve inference [12].

**2.2. Radar Sensors (RSs).** There are two radar sensor types based on its mode operation (the transmission method): Frequency Modulation Continuous Wave (FMCW) and pulsed radar [8]. FMCWs send a continuous signal whereas pulsed radars send a pulse each time period $T_b$ [13]. Also, there are three types of radar sensors in terms of its transmitter and receiver antenna positions: monostatic, bi-static, and multi-static radar sensors [13].

With the benefits mentioned above, it is simple to determine the target position. To localize a target, there are two methods: range based and range free [13]. Each method contains many techniques. Range based, for instance, has Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA), and Received Signal Strength Indicator (RSSI) techniques to identify the range [11]. Since this work will be based on the active sensing, range based-TOA is utilized. After measuring TOA, a target range can be obtained by Equation (1):

$$R = CT_p/2 \tag{1}$$

where $R$ represents the range, $C$ represents the speed of light, and $T_p$ is time of arrival of the sent signal. The frequency of industrial radar sensors ranges from 2.4 GHz-75 GHz [13,14].

## 3. Proposed Monitoring System.

The proposed monitoring system deals with fixed targets, and it is divided into four stages: (1) clustering the network whose parameters are mentioned in [7] via the modified HEED routing protocol, (2) preprocessing radar sensor measurements that gathered from a cluster via Kalman filter, (3) determining and identifying the 3D target position that are the initial value via trilateration/multilateration algorithm and non-linear least square method respectively, (4) classifying the target that could be a vehicle or drone via fuzzy logic. All parameters are not optimized, such as the number of sensors, and the area covered. Figure 1 illustrates the block diagram of the system.

In order to illustrate how this proposed system functions, one cluster of three radar sensors is shown in Figures 2(a) and 2(b) with a distinct target; by modifying HEED routing protocol, clustering has been implemented [7]. For simplification purposes, Figure 2 depicts radar sensors involving in identifying a target without displaying the head cluster.

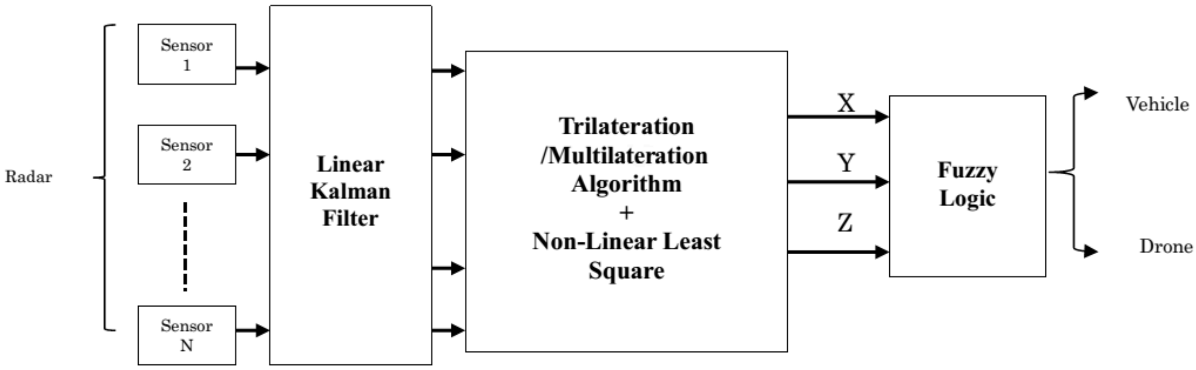
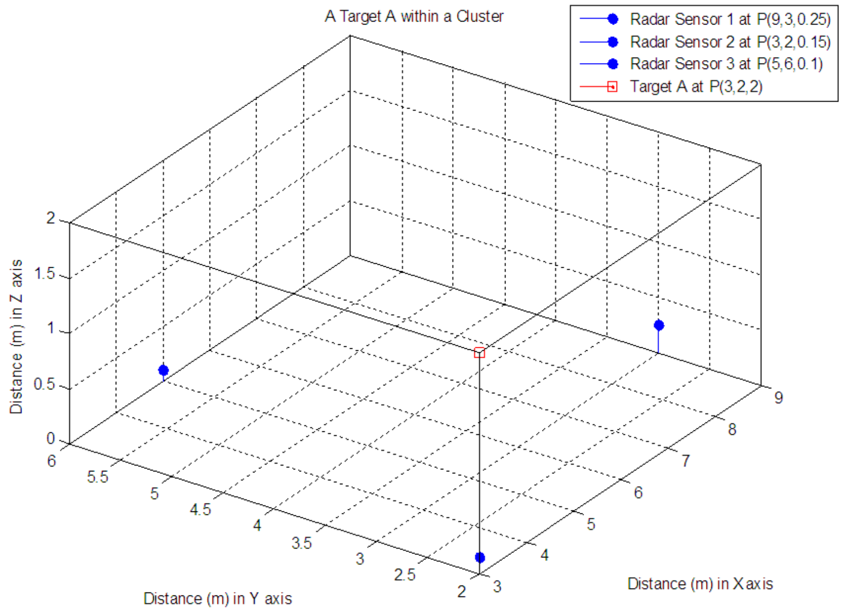
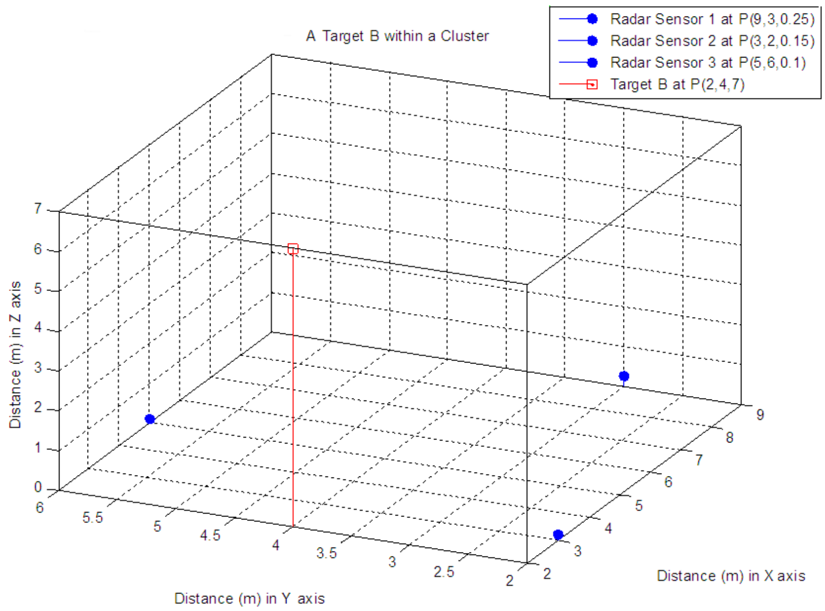



Figure 1. The block diagram of the whole system




(a)




(b)

Figure 2. A cluster of 3 RSs with a target: (a) Target A, and (b) Target B

3.1. **Linear Kalman Filter (LKF).** Kalman filters apply predictor-corrector estimators "the state $X \in R^n$" [3]. This estimation could be based on linear or non-linear systems. Each kind requires different approaches of Kalman filters. In this work, the linear Kalman filter has been chosen since the measurements are mixed with noise. Therefore, the linear Kalman filter algorithm is explained. This algorithm comprises prediction (a *priori*) and correction (a *posteriroi*) value [3] as shown in Equation (2):

$$X_{k+1} = AX_k + W_k \tag{2}$$

where $X_k$ refers to the state vector $(N \times 1)$, while $A$ refers to the transition state matrix of the process from the state at $K$ to $K+1$ $(N \times M)$. Also, $W_k$ represents the white Gaussian noise $(N \times 1)$ for the process. For the observation equation, it can be written as shown in Equation (3):

$$Z_k = HX_k + V_k \tag{3}$$

where $Z_k$ refers to actual measurements of $X$ $(M \times 1)$, while $H$ refers to the connection matrix of the state and measurement vector $(M \times N)$. Furthermore, $V_k$ represents the white Gaussian noise $(M \times 1)$ for the measurements. Both $Q$ and $R$ matrices that represent the covariance of noise can be written as displayed in Equations (4) and (5):

$$Q = E\left[W_k \;\; W_k^T\right] \tag{4}$$

$$R = E\left[V_k \;\; V_k^T\right] \tag{5}$$

3.2. **T/M algorithm [9].** Once a target is detected by the cluster, radar sensor measurements are preprocessed via Kalman filter to minimize the noise at the base station. With their known 3D locations, the base station calculates the 3D target position by applying T/M algorithm. This can be recognized by Equation (6) [9,10]:

$$\widehat{D}_i = \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2}, \quad i = 1, 2, \ldots, N \tag{6}$$

To determine the 3D position, the number of nodes $(N)$ should be equal to or higher than 3. In case that the cluster has the minimum number $(N = 3)$, Equation (6) can be extended as follows:

$$\widehat{D}_1 = \sqrt{(x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2} \tag{7}$$

$$\widehat{D}_2 = \sqrt{(x-x_2)^2 + (y-y_2)^2 + (z-z_2)^2} \tag{8}$$

$$\widehat{D}_3 = \sqrt{(x-x_3)^2 + (y-y_3)^2 + (z-z_3)^2} \tag{9}$$

Equations (7), (8), and (9) can be written in a matrix form as the following equation:

$$A \begin{pmatrix} x \\ y \\ z \end{pmatrix} = b \tag{10}$$

where matrix $A$ and $b$ are shown in Equations (11) and (12) respectively:

$$A = \begin{pmatrix} x_1 - x_2 & y_1 - y_2 & z_1 - z_2 \\ x_2 - x_3 & y_2 - y_3 & z_2 - z_3 \end{pmatrix} \tag{11}$$

$$b = 0.5 * \begin{pmatrix} \widehat{D}_2^2 - \widehat{D}_1^2 + x_1^2 - x_2^2 + y_1^2 - y_2^2 + z_1^2 - z_2^2 \\ \widehat{D}_3^2 - \widehat{D}_2^2 + x_2^2 - x_3^2 + y_2^2 - y_3^2 + z_2^2 - z_3^2 \end{pmatrix} \tag{12}$$

Finally, the target position $(x, y, z)$ can be approximately calculated as shown in Equation (13):

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = A^T \left(A^T A\right)^{-1} b \tag{13}$$

The output of this stage is considered an input of the next stage – non-linear least square method.

3.3. **Non-Linear Least Square method (NLLS method).** In general, this method minimizes the sum of square of a function as stated in Equation (14):

$$\min_{x} \ f(x) = \sum_{i=1}^{N} f_i(x)^2 \tag{14}$$

where $f(x)$ is the non-linear function [12]. In the proposed monitoring system, this function represents 3D distance equation as shown in Equation (6). The errors of sum square of this function can be reduced. Therefore, Equation (2) becomes as in Equation (15) [9]:

$$F(x,y,z) = \sum_{i=1}^{N} \left(D_i - \widehat{D}_i\right)^2 \tag{15}$$

where $\widehat{D}_i$ is the approximate distance between the $i$th sensor node and the target, while $D_i$ is the distance measured via sensors. Also, $N$ equals the sensor number involved to determine the target position. Equation (15) can be rewritten as stated in Equation (16) [10]:

$$f_i(x,y,z) = \sum_{i=1}^{N} \left(\sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} - \widehat{D}_i\right)^2 \tag{16}$$

According to the T/M algorithm, the value of $(x,y,z)$ can approximately be obtained. This algorithm provides a decent estimate in order to gain the optimal solution of $(x,y,z)$; that is the output of the nonlinear least square method. Pursuing with this method requires that $f_i$ should be greater than zero and $N$ is greater than 3. Based on that, differentiating partially Equation (16) with respect to $x$, $y$, and $z$ aids to write the Jacobian matrix as shown in Equation (17):

$$J = \begin{pmatrix} \dfrac{\partial f_1}{\partial x} & \dfrac{\partial f_1}{\partial y} & \dfrac{\partial f_1}{\partial z} \\ \dfrac{\partial f_2}{\partial x} & \dfrac{\partial f_2}{\partial y} & \dfrac{\partial f_2}{\partial z} \\ \vdots & \vdots & \vdots \\ \dfrac{\partial f_N}{\partial x} & \dfrac{\partial f_N}{\partial y} & \dfrac{\partial f_N}{\partial z} \end{pmatrix} \tag{17}$$

In addition, Equations (18) and (19) introduce vectors $f$ and $R$ respectively, and the Newton iteration will be implemented to calculate $(x,y,z)$ as described in Equation (20):

$$\vec{f} = [f_1 \ \ f_2 \ \ \dots \ \ f_N]' \tag{18}$$

$$\vec{R} = [x \ \ y \ \ z]' \tag{19}$$

$$\vec{R}_{\{k+1\}} = \vec{R}_{\{k\}} - \left(J_{\{k\}}^T J_{\{k\}}\right)^{-1} J_{\{k\}}^T \vec{f}_{\{k\}} \tag{20}$$

$$J^T J = \begin{pmatrix} \sum\limits_{i=1}^{N} \dfrac{(x-x_i)^2}{\left(f_i + \widehat{D}_i\right)^2} & \sum\limits_{i=1}^{N} \dfrac{(x-x_i)(y-y_i)}{\left(f_i + \widehat{D}_i\right)^2} & \sum\limits_{i=1}^{N} \dfrac{(x-x_i)(z-z_i)}{\left(f_i + \widehat{D}_i\right)^2} \\ \sum\limits_{i=1}^{N} \dfrac{(x-x_i)(y-y_i)}{\left(f_i + \widehat{D}_i\right)^2} & \sum\limits_{i=1}^{N} \dfrac{(y-y_i)^2}{\left(f_i + \widehat{D}_i\right)^2} & \sum\limits_{i=1}^{N} \dfrac{(x-x_i)(z-z_i)}{\left(f_i + \widehat{D}_i\right)^2} \\ \sum\limits_{i=1}^{N} \dfrac{(x-x_i)(z-z_i)}{\left(f_i + \widehat{D}_i\right)^2} & \sum\limits_{i=1}^{N} \dfrac{(x-x_i)(y-y_i)}{\left(f_i + \widehat{D}_i\right)^2} & \sum\limits_{i=1}^{N} \dfrac{(z-z_i)^2}{\left(f_i + \widehat{D}_i\right)^2} \end{pmatrix} \tag{21}$$

$$J^T f = \begin{pmatrix} \sum_{i=1}^{N} \frac{(x - x_i) f_i}{f_i + \widehat{D}_i} \\ \sum_{i=1}^{N} \frac{(y - y_i) f_i}{f_i + \widehat{D}_i} \\ \sum_{i=1}^{N} \frac{(z - z_i) f_i}{f_i + \widehat{D}_i} \end{pmatrix} \tag{22}$$

3.4. **Fuzzy logic.** According to [1-3], fuzzy logic can make inference about uncertainty events regardless which type of fuzzy logic has been applied. This inference helps systems to make the approximate decision. Based on the previous stage output, fuzzy logic can be applied so that it is simple to classify the target. As this paper involved in localizing different targets, a vehicle and drone have been utilized. Consequently, the height $z(h)$ that represents one of differences between them is considered the membership function of $z$ coordinates. With normalization, type-2 fuzzy inference system is able to deal with this. Dividing the output into four intervals $[0, 0.1]$, $[0.1, 0.25]$, $[0.25, 0.5]$, and $[0.5, 1]$ can help make decisions. These intervals exhibit the likelihood value of target type. For example, $[0, 0.1]$ has a high possibility of the vehicle target being a vehicle and a low possibility of the target being a drone unless flying at low altitudes. Similarly, $[0.5, 1]$ has a high probability of the target being a drone. However, $[0.1, 0.25]$ represents a high to medium possibility of the target being a vehicle, while $[0.25, 0.5]$ ranges from a medium to high probability of being the drone target as shown in Figure 3.

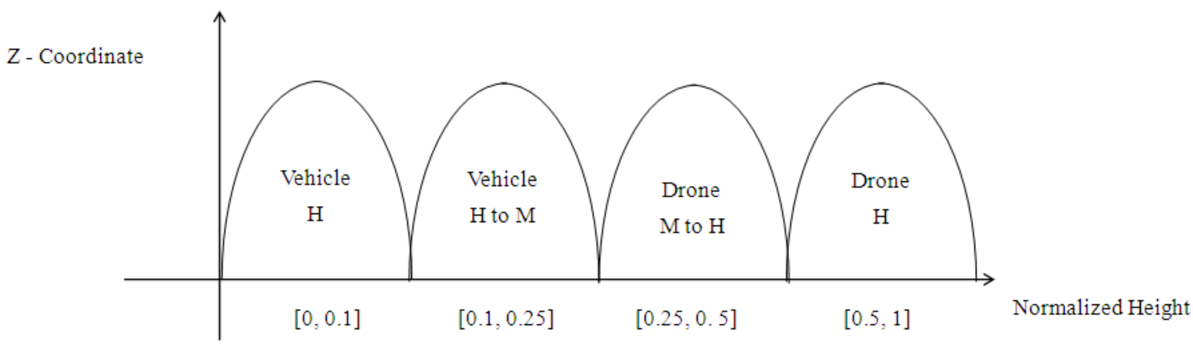



FIGURE 3. Type-2 fuzzy logic of classification targets

4. **Simulation Results and Discussions.** 100 UWB-Radar sensors deployed randomly according to modified HEED routing protocol across an outdoor field of 200 m $*$ 200 m. This paper has examined a scenario that a target exists within only one cluster range to evaluate the performance of the monitoring system. Figure 4(a) shows the 3 radar sensor measurements of the drone target range. Similarly, the vehicle target range is depicted in Figure 4(b). It is observed from Figure 4 that all measurements are not precise values. For this reason, these measurements need to be filtered via Kalman filter as shown in Figure 5.

In addition, it is noticed that when the target height increases, the result of the T/M algorithm can be impacted specifically in Z components. Thus, it affects the convergence process of the NLLS method. Consequently, it slightly degrades the performance of the whole system.

5. **Conclusions.** Detecting the fixed target position in 3D and classifying a target based on a proposed monitoring system of an outdoor field (200 m $*$ 200 m) with 100 UWB radar sensors and a base station was achieved. After clustering based on modified HEED routing protocol, each cluster detects any target within its range and sends its sensor

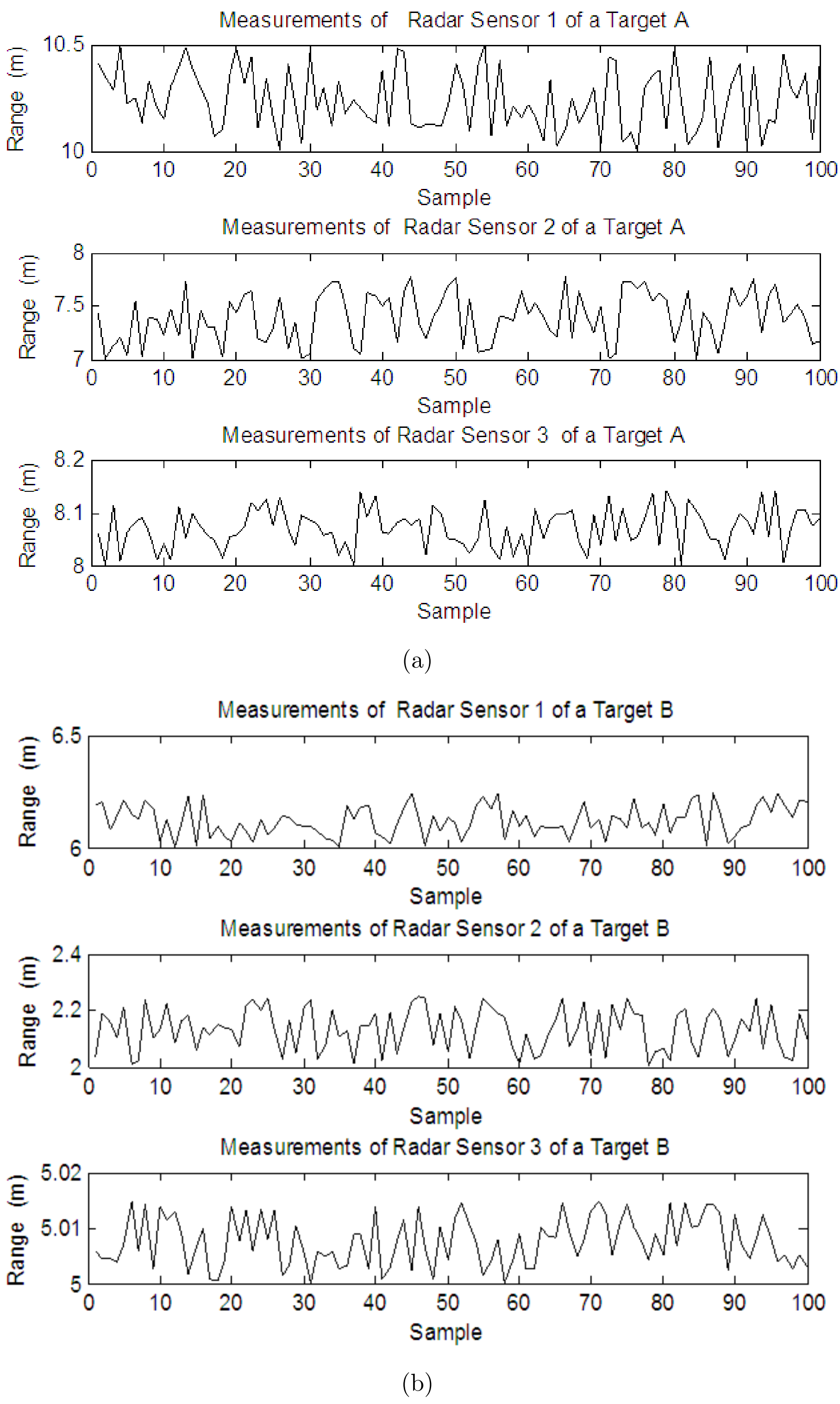



FIGURE 4. Measurements of three radar sensors for: (a) drone, and (b) vehicle

data to the base station where all sensor data noise will be reduced via linear Kalman filter. By involving sensor measurements, the ability to detect a 3D position for a fixed target was precisely achieved. Applying type-2 fuzzy logic has greatly classified the target. Simulation results show that the overall system performance of detecting and classifying the target position and type was successful. In the next work, an extended Kalman filter should be applied instead of non-linear least square with a moving target.

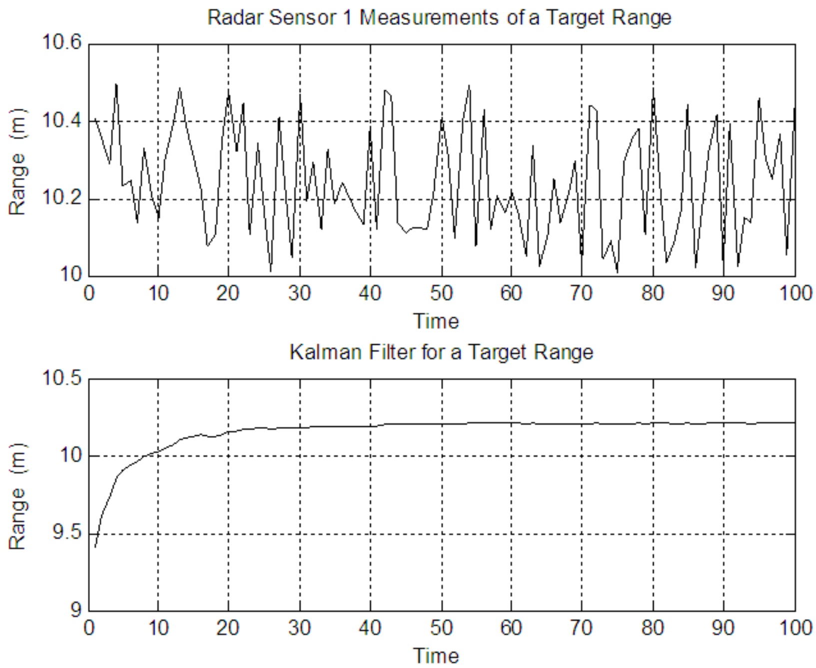



FIGURE 5. Applying Kalman filter on RS-1 measurements

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