A Multi-source Report-level Simulator for Fusion Research

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Abstract

The Multi-source Report-level Simulator (MRS) is a tool developed by Veridian Systems as part of its Model-adaptive Multi-source Track Fusion (MMTF) effort under DARPA's DTT program. MRS generates simulated multisensor contact reports for GMTI, HUMINT, IMINT, SIGINT, UGS, and video. It contains a spatial editor for creating ground tracks along which vehicles move over the terrain. Vehicles can start, stop, speed up, or slow down. The spatial editor is also used to define the locations of fixed sensors such as UGS and HUMINT observers on the ground, and flight paths of GMTI, IMINT, SIGINT, and video sensors in the air. Observation models characterize each sensor at the report level in terms of their operating characteristics (revisit rate, resolution, etc.) measurement errors, and detection/classification performance (i.e., P_d, N_{fa}, P_{cc}, and P_{id}). Contact reports are linked to ground truth data to facilitate the testing of track/fusion algorithms and the validation of associated performance models.

Introduction

Ground vehicle and sensor simulators are important tools used in the development of tracking, fusion, and related exploitation algorithms. An important consideration in developing and testing track/fusion systems is the creation of integrated multi-sensor test data sets (i.e., contact reports with ground truth) at an appropriate level of fidelity. Under DARPA's Dynamic Tactical Targeting (DTT) program, Veridian Systems is developing a Model-adaptive Multi-source Track and Fusion (MMTF) system for exploiting data from ISR and organic sensors including GMTI, HUMINT, IMINT, SIGINT, UGS, and video. In support of this work we have created a tool known as the Mult-sensor Report-level Simulator (MRS) for generating simulated multi-sensor contact reports and ground truth. Like Toyon's Ground Vehicle Simulator [1], MRS simulates ground vehicle tracks, but uses relatively simple motion models. Striking a balance between low level signal/pixel level sensor simulations and high level exploitation models (e.g., those used in SLAMEN [2]), MRS simulates sensor/exploitation processes at an intermediate level of fidelity consistent with the models used in track/fusion systems like MMTF [3]. At this level, MRS produces simulated contact reports containing measurements of a ground vehicle's location, observed features (e.g., size, shape, speed, emissions, etc.), and classification/ID (as produced by an upstream ATR algorithm), as well as estimates of the associated measurement errors and detection/classification performance. This information is provided in the form of flat files (ASCII text) which can be easily imported into most tracking/fusion applications.

Architecture

The top-level MRS functional architecture is shown in Fig. 1. The ground truth specification file defines ground tracks, vehicles, and the motion of vehicles along the ground tracks. Vehicles can start, stop, speed up, or slow down. An interactive spatial editor is provided for creating ground tracks and sensor platform flight path files and defining the locations of fixed sensors on the ground (e.g., HUMINT and UGS). Sensor/observation models consist of two parts: the math model (e.g., a 2-D positional error covariance matrix), and the parameters of the math model (e.g., range and cross-range errors, sensor azimuth). Sensor observation model specification files define sensor locations (static, or moving along pre-defined flight paths), the observability of ground vehicles based on a digital elevation model (DEM) of the terrain, and the parameters of the respective sensor/observation models. Ground truth and sensor observation model specification files drive the sensor math models embedded within a discrete-time simulator to produce contact reports.

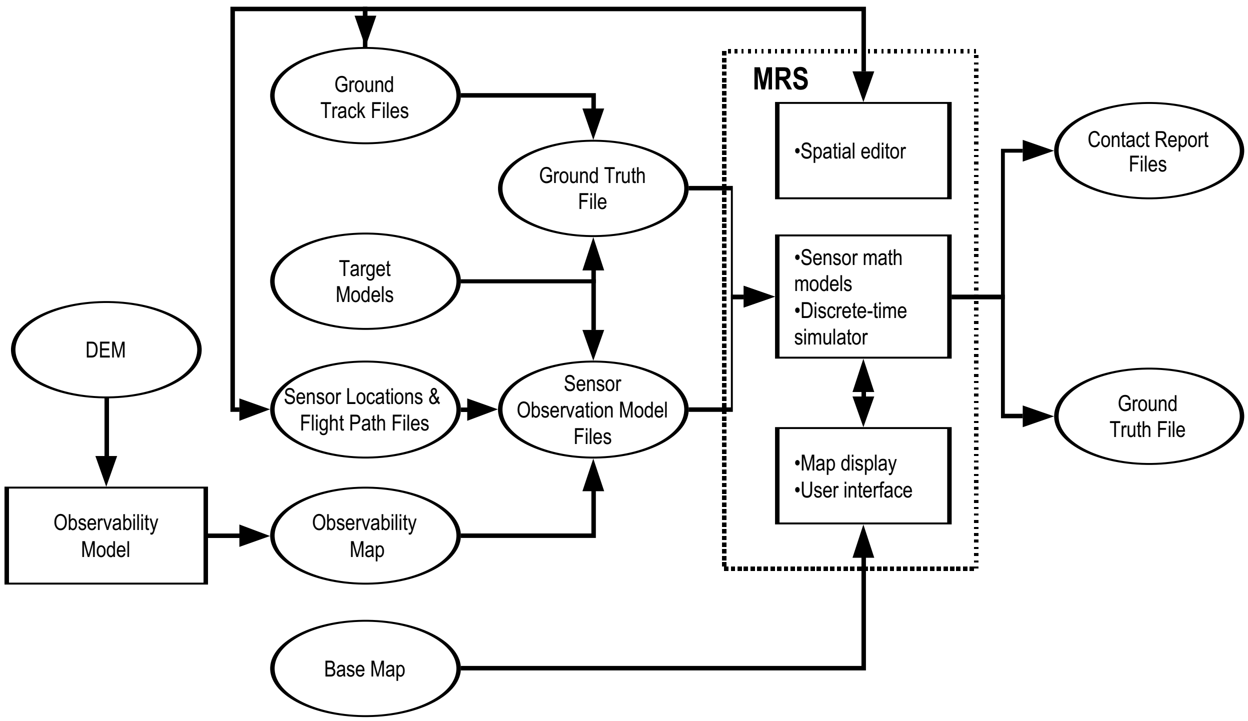

Fig. 1 MRS top-level functional architecture

Ground Truth Generator

Simulations occur within a playbox whose spatial extent and origin within a larger coordinate system are defined in the ground truth specification file (Table 1). Ground truth data are generated at a fixed rate. Locations are quantized to a grid defined by the spatial resolution. The motion of each group of ground vehicles is defined by a separate track file. A group consists of one or more vehicles, which can be arranged in a column when moving along roads, or be randomly dispersed when moving cross-country. In MRS it is up to the user to make sure that the velocities specified in track files are consistent with the types of vehicles represented.

Table 1 Ground truth specification file format.

Field Name	Data Type	Enumeration
Width of play box (m)	integer	> 0
Height of play box (m)	integer	> 0
X origin (m)	integer	
Y origin (m)	integer	
Resolution (m)	integer	≥ 1
Sample time (sec)	integer	≥ 1
Background image name (PICT)	string	filename
Number of g.t. tracks	integer	≥ 1
Name of track 1	string	filename
Start time (sec)	integer	≥ 0
Formation	string	{column, dispersed}
Spacing (m)	integer	≥ 0
Number of vehicles	integer	≥ 1
ID of first vehicle	string	<predefined vehicle ID>
	etc...	

Ground vehicle and sensor flight paths are defined by a set of N waypoints $\{P_n\}$ that give the desired location and velocity of an entity, $P_n = (x_n, y_n, v_n)$, either on the ground, or at a given altitude. The path between P_n and P_{n+1} is defined by a b-spline:

$$x(r) = \tfrac{1}{6}\begin{bmatrix} r^3 \\ r^2 \\ r \\ 1 \end{bmatrix}\begin{bmatrix} -1 & 3 & -3 & 1 \\ 3 & -6 & 3 & 0 \\ -3 & 0 & 3 & 0 \\ 1 & 4 & 1 & 0 \end{bmatrix}\begin{bmatrix} x_{n-1} \\ x_n \\ x_{n+1} \\ x_{n+2} \end{bmatrix}, \quad y(r) = \tfrac{1}{6}\begin{bmatrix} r^3 \\ r^2 \\ r \\ 1 \end{bmatrix}\begin{bmatrix} -1 & 3 & -3 & 1 \\ 3 & -6 & 3 & 0 \\ -3 & 0 & 3 & 0 \\ 1 & 4 & 1 & 0 \end{bmatrix}\begin{bmatrix} y_{n-1} \\ y_n \\ y_{n+1} \\ y_{n+2} \end{bmatrix} \tag{1}$$

or

$$\begin{aligned} x(r) &= \tfrac{1}{6}\left[x_{n-1}(-r^3+3r^2-3r+1) + x_n(3r^3-6r^2+4) + x_{n+1}(-3r^3+3r^2+3r+1) + x_{n+2}r^3\right] \\ y(r) &= \tfrac{1}{6}\left[y_{n-1}(-r^3+3r^2-3r+1) + y_n(3r^3-6r^2+4) + y_{n+1}(-3r^3+3r^2+3r+1) + y_{n+2}r^3\right] \end{aligned} \tag{2}$$

for $0 \le r \le 1$. Position along the b-spline is interpolated by stepping the index

$$r(j+1) = r(j) + \frac{v(j)\delta t}{d_{n,n+1}} \tag{3}$$

where δt is the sample rate, $d_{n,n+1}$ is the distance between P_n and P_{n+1}, and

$$v(j) = [1 - r(j)]v_n + r(j)v_{n+1} \tag{4}$$

is the interpolated velocity (speed) along the spline curve. The direction of motion along the spline is

$$\theta(r) = \tan^{-1}\left[\frac{\partial y(r)}{\partial r}\Big/\frac{\partial x(r)}{\partial r}\right]. \tag{5}$$

The b-spline is smoother than other cubic forms with continuous first and second derivatives, which makes it a good choice for modeling both ground vehicle and sensor platform motion. Fig. 2 is a portion of a ground vehicle track showing the waypoints and interpolated path.

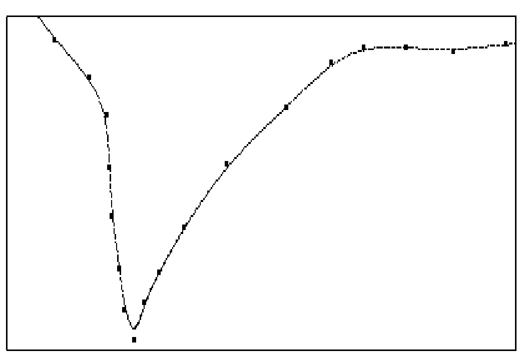

Fig. 2 Example of MRS ground track

The following sections describe the GMTI, HUMINT, IMINT, SIGINT, UGS, and video sensor observation models used in MRS.

Ground Moving Target Indicator (GMTI) Radar Model

In our model GMTI radars are assumed to fly at a constant altitude. Multiple GMTI radars may be defined, where the position of each radar platform as a function of time is defined by its own track file. Parameters of the GMTI sensor observation model are listed in Table 2.

Table 2 GMTI sensor observation model specification file format

	Data Type	Enumeration
Sensor resolution (m/pixel)	integer	> 0
Range error (m)	float	≥ 0
Cross-range error (m)	float	≥ 0
Minimum detectable velocity (m/sec)	float	≥ 0
Revisit time (sec)	integer	> 0
Revisit time distribution	string	{constant, exponential}
Probability of Detection, Pd	float	[0.0,1.0]
Number of false alarms, Nfa	float	≥ 0
Probability of Correct Classification, Pcc	float	[0.0,1.0]
Number of GMTI platforms	integer	> 0
Track file for first platform	string	filename
Start time for first platform (sec)	integer	> 0
Bias error X (m)	float	≥ 0
Bias error Y (m)	float	≥ 0
Observability map array (raw 8 bit file)	string	filename
Width of obs. map array	integer	>0
Height of obs. map array	integer	>0
etc.		

Sensor resolution – For a standoff sensor like a GMTI, resolution can be treated as a constant parameter. Report coordinates are quantized to multiples of the sensor resolution in the ground coordinate space.

Range and cross-range errors define the size of the positional error ellipse. The orientation of the ellipse varies as a function of the sensor's location relative to the moving target. In range vs. cross-range coordinates the covariance matrix is:

$$\mathbf{M} = \begin{bmatrix} \sigma^2_{range} & 0 \\ 0 & \sigma^2_{cross-range} \end{bmatrix} \tag{6}$$

where the range error is a parameter of the radar, and the cross-range error is a function of the beam-width and range. Both are assumed constant over the radar sweep. In geographic coordinates, the covariance matrix is rotated by the azimuth angle of the sensor platform relative to the moving target

$$\mathbf{M}_{geo} = \begin{bmatrix} \sigma^2_{range}\cos^2\theta + \sigma^2_{cross-range}\sin^2\theta & \sin\theta\cos\theta\sigma^2_{range} - \sin\theta\cos\theta\sigma^2_{cross-range} \\ \sin\theta\cos\theta\sigma^2_{range} - \sin\theta\cos\theta\sigma^2_{cross-range} & \sigma^2_{range}\sin^2\theta + \sigma^2_{cross-range}\cos^2\theta \end{bmatrix} \tag{7}$$

Minimum detectable velocity – Let $\mathbf{v}$ be the velocity vector of a moving target in the ground reference frame. If $\mathbf{x}$ and $\mathbf{y}$ are the locations of the target and the sensor, the component of the target's velocity in the direction of the radar is

$$\upsilon = \mathbf{v}^T(\mathbf{x}-\mathbf{y}) \Big/ \sqrt{(\mathbf{x}-\mathbf{y})^T(\mathbf{x}-\mathbf{y})} \tag{8}$$

If a target's velocity, $\upsilon < \upsilon_0$, where υ_0 is the minimum detectable velocity (MDV) of the radar, the target is not detected by the radar.

Probability of detection and false alarm rates – The probability of detection (P_d) and number of false alarms per sq. km. (N_{fa}) are treated as constant parameters. P_d gives the probability of detecting objects whose radial velocity is greater than the MDV, and are observable by (in line of sight of) the radar. P_d may thus be reduced as a vehicle slows, or is shadowed by the terrain.

Revisit rate may be either uniform or vary randomly according to an exponential distribution. For a uniform revisit rate, the revisit time Δt is some integer number of seconds. For a random revisit rate, the distribution of revisit times is, based on an exponential distribution model,

$$f(\Delta t) = \beta e^{-\beta \Delta t} \tag{9}$$

where $1/\beta$ is equal to the average number of revisits over time.

Probability of correct classification - Discrete target features extractable from GMTI are modeled using confusion matrices. Currently GMTI provides one feature, tracked-wheeled, with possible values: {tracked, wheeled, other}. The confusion matrix is:

$$\begin{bmatrix} P_{tracked|tracked} & P_{wheeled|tracked} & P_{other|tracked} \\ P_{tracked|wheeled} & P_{wheeled|wheeled} & P_{other|wheeled} \\ P_{tracked|other} & P_{wheeled|other} & P_{other|other} \end{bmatrix} = \begin{bmatrix} P_{cc} & \tfrac{1}{2}(1-P_{cc}) & \tfrac{1}{2}(1-P_{cc}) \\ \tfrac{1}{2}(1-P_{cc}) & P_{cc} & \tfrac{1}{2}(1-P_{cc}) \\ \tfrac{1}{2}(1-P_{cc}) & \tfrac{1}{2}(1-P_{cc}) & P_{cc} \end{bmatrix} \tag{10}$$

where P_{cc} is a constant provided by the user.

Bias error represents the navigational uncertainty of the sensor platform. The x and y components of the bias error are constant positional offsets added to all report locations in the sensor track. Each sensor can have a different bias error.

Observability – Let ϕ be the depression angle of the GMTI, which depends on standoff range and altitude. Assume for the sake of discussion that the GMTI platform is located to the east (azimuth angle θ=90°), and let $z(x, y)$ be the elevation map. The observability map is defined as follows:

$$o(x,y,\phi) = \begin{cases} 1, \text{ } if \text{ } x\sin\phi + Vz(x,y)\cos\phi = \max\limits_{x' \le x}\{x'\sin\phi + Vz(x',y)\cos\phi\} \\ 0, \text{ } otherwise \end{cases} \tag{11}$$

where V is the vertical exaggeration (scale). In general, if the sensor azimuth angle is θ, the elevation map is rotated so the look direction is along the +x axis, the observability map is computed, and the result rotated back. The average observability over a surveillance orbit is the average of the observability maps over all sensor locations in the orbit. For a N locations (e.g., spaced at 1 degree intervals in azimuth),

$$E[o(x,y)] = \frac{1}{N}\sum_{\theta_n} o(x,y,\theta_n) \tag{12}$$

The average observability, normalized to the range [0,1], is used to locally modulate the probability of detection.

Unattended Ground Sensor Model

UGS are assumed to operate in clusters of three sensors. The locations of the sensors in each cluster are stored in a separate file. Parameters of the UGS sensor observation model specification file are listed in Table 3.

Table 3 MRS UGS sensor observation model specification file format

Field Name	Data Type	Enumeration
Bearing measurement error (deg.)	float	> 0
Revisit time (sec)	integer	> 0
Revisit time distribution	string	{constant, exponential}
Pd vs. range table (low-level)	string	filename
Pd vs. range table (high-level)	string	filename
Pcc vs. range table (low-level)	string	filename
Pcc vs. range table (high-level)	string	filename
Number of UGS sensor clusters	integer	> 0
UGS locations file for the first cluster	string	filename
etc.		

Positional error covariance assumes $M = 3$ sensors located at (x_1, y_1), (x_2, y_2), and (x_3, y_3), each with i.i.d. bearing measurement errors of variance e^2. Assuming spherical propagation (ideal conditions), the positional covariance at location (x_0, y_0) is [4]:

$$e^2\begin{bmatrix} \frac{\sin^2\theta_1}{r_1^2}+\frac{\sin^2\theta_2}{r_2^2}+\frac{\sin^2\theta_3}{r_3^2} & -\frac{\sin\theta_1\cos\theta_1}{r_1^2}-\frac{\sin\theta_2\cos\theta_2}{r_2^2}-\frac{\sin\theta_3\cos\theta_3}{r_3^2} \\ -\frac{\sin\theta_1\cos\theta_1}{r_1^2}-\frac{\sin\theta_2\cos\theta_2}{r_2^2}-\frac{\sin\theta_3\cos\theta_3}{r_3^2} & \frac{\cos^2\theta_1}{r_1^2}+\frac{\cos^2\theta_2}{r_2^2}+\frac{\cos^2\theta_3}{r_3^2} \end{bmatrix}^{-1} \tag{13}$$

where

$$\begin{aligned} \theta_m &= \tan^{-1}\left(y_0 - y_m / x_0 - x_m\right) \\ r_m &= \sqrt{\left(y_0 - y_m\right)^2 + \left(x_0 - x_m\right)^2} \end{aligned}. \tag{14}$$

Probability of detection and false alarm rates – The probability of detection (P_d) depends on range, and is computed from tables at run-time. Two tables are required: one specifies P_d vs. range for lightweight targets (e.g., BMP-1), the other specifies P_d vs. range for heavyweight targets (e.g., MAZ-543). The tables give the P_d at different ranges; e.g.,

0	0.7
500	0.5
1000	0.3
2000	0

where intermediate values are interpolated. For UGS, N_{fa} is assumed to be zero.

Probability of correct classification – Classification errors of UGS target features are represented in form of confusion matrices parameterized by the average probability of correct classification (P_{cc}). As with P_d, P_{cc} varies with range and is computed from tables at run-time. Table 4 gives the enumeration of values for representative UGS features [6,7].

Table 4 UGS features and values

Feature	Values
Number of axles	{2,3,4,6,8,other}
Number of cylinders	{6,8,12,other}
RPM	{2000,2100,2600,3200,3400,3600,other}
Weight	{heavy, light, other}
Tracked-Wheeled	{tracked, wheeled, other}

Revisit rate – Typically we assume a constant approximate 1 second revisit (reporting) rate for UGS.

UGS are placed by knowledge of an implicit near optimal placement rule based on an explicit optimal theoretical model [4] (not currently implemented), which defines locations of minimum and locations, in specific regions, of both minimum or near minimum target location error estimates with respect to the sensor locations. This implicit rule also provides guidance for placement of sensors with respect to anticipated target trajectories.

SIGINT Model

We assume an angle of arrival (AOA) system where groups of three measurements at a time are used to generate a positional error estimate. This allows us to use the same positional error math model as UGS. Parameters of the SIGINT sensor observation model specification file are listed in Table 5.

Table 5 MRS SIGINT sensor observation model specification file format

Field Name	Data Type	Enumeration
Bearing measurement error (deg.)	float	> 0
Revisit time (sec)	integer	> 0
Revisit time distribution	string	{constant, exponential}
Pd	float	[0.0,1.0]
Sample spacing (m)	float	≥ 0
Number of SIGINT platforms	integer	> 0
Track file for first platform	string	filename
Start time for first platform (sec)	integer	> 0
etc.		

Positional error – Unlike UGS, where the sensors are fixed, SIGINT measurements are generated at a specified revisit rate along a flight path at three locations: the current location (x_1, y_1) plus two previous locations (x_2, y_2), and (x_3, y_3) that are a specified sample spacing Δd apart

$$\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \approx \sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2} \approx \Delta d \tag{15}$$

In MRS the first SIGINT report is generated after the platform has moved at least $2\Delta d$ from its initial position.

In this system the measurements are taken sequentially and stored (along with precise platform locations) over the time instants corresponding to the platform motion over the $2\Delta d$ distances. After the third measurement is taken the target position estimate error is computed using Eq. 13. As in the case of UGS, an implicit sensor placement rule governs the selected platform flight profile.

Probability of detection and false alarm rates – Like GMTI, SIGINT is a standoff sensor. Thus range does not vary significantly over the simulated FOV and so P_d and N_{fa} can be treated as constants.

SIGINT features - Three target features: emitter frequency, emitter power, and pulse repetition frequency (PRF) are currently modeled. Feature values are assumed to be uniformly distributed within specified ranges for each target type; e.g., for a T-72 tan the ranges are emitter frequency: 30-76 Mhz, emitter power: 28-32 watts, and pulse repetition frequency 0 (0-0).

IMINT Model

IMINT is assumed to be a wide-angle, standoff sensor. In contrast to GMTI, targets are not detected if they are moving faster than a given speed. Since the number of revisits are relatively few in number compared to the other sensors, the number and parameters of the collections are specified explicitly instead of using a flight path model. Parameters of the IMINT sensor observation model specification file are listed in Table 6.

Table 6 MRS IMINT sensor observation model specification file format

Field Name	Data Type	Enumeration
Number of revisits	integer	> 0
Sensor 1	string	{SAR,EO}
Revisit time 1	integer	≥ 0
Sensor resolution (m/pixel)	integer	> 0
Range error (m)	float	≥ 0
Cross-range error (m)	float	≥ 0
Maximum detectable speed	float	≥ 0
Pd	float	[0.0,1.0]
Nfa	float	≥ 0
Pid	float	[0.0,1.0]
Sensor 2	integer	> 0
etc.		

IMINT features – IMINT provides measurements of target length and width. Let Δ_{range} and $\Delta_{cross-range}$ be the range and cross-range resolutions. In one dimension, the uncertainty (variance) in location of a point due to quantization is (assuming a uniform error distribution):

$$\frac{1}{\Delta}\int_{-\Delta/2}^{\Delta/2} r^2 dr = \frac{\Delta^2}{12}. \tag{16}$$

Since the range and cross-range errors are independent the covariance is

$$\frac{1}{12}\begin{bmatrix} \Delta^2_{range} & 0 \\ 0 & \Delta^2_{cross-range} \end{bmatrix} \tag{17}$$

and the rms error is $\varepsilon = \sqrt{\frac{1}{12}(\Delta^2_{range} + \Delta^2_{cross-range})}$. The rms error in estimating the length (or width) of a feature is 2ε.

Probability of identification – Each IMINT sensor is assumed to contain an automated target recognition (ATR) capability, with average probability of correct ID (P_{id}). Like misclassification error, errors in incorrectly identifying a target are modeled by a confusion matrix with elements

$$P_{i|j} = \begin{cases} P_{id},\, i = j \\ (1 - P_{id})/N,\, i \neq j \end{cases} \tag{18}$$

where N is the number of target IDs.

Video Model

Unlike GMTI and SIGINT, which are wide-angle, standoff sensors, the resolution of a video report depends on the range of the target. Given its limited field of view, the video sensor must be aimed at a particular point on the ground. The location of the aim point is specified by a ground track file. Parameters of the video sensor observation model specification file are listed in Table 7.

Table 7 MRS video sensor observation model specification file format

Field Name	Data Type	Enumeration
IFOV (radians)	float	> 0
Aim angle error (radians)	float	≥ 0
Sensor altitude (meters)	float	> 0
Revisit time (sec)	integer	> 0
Revisit time distribution	string	{constant, exponential}
Nfa (FA per sq. km.)	float	≥ 0
Swath length (pixels)	integer	> 0
Swath width (pixels)	integer	> 0
Pd vs. resolution table	string	filename
Pd vs. incidence angle table	string	filename
Pid vs. resolution table	string	filename
Pid vs. incidence angle table	string	filename
Number of video platforms	integer	> 0
Platform track file for first platform	string	filename
Start time of track (sec)	integer	≥ 0
Ground track file (aim point)	string	filename
etc.		

Resolution is a function of the instantaneous field of view (IFOV) of the video sensor, its distance from the target, and the incidence angle. Video is assumed to have a fixed focal length, and constant IFOV. The range and cross-range resolutions are:

$$\Delta_{range} = \alpha r / \sin\phi$$
$$\Delta_{cross-range} = \alpha r \tag{19}$$

where α is the IFOV (in radians), r is range, and ϕ is incidence angle. When the sensor is overhead, $\phi = 90°$, $\Delta_{range} = \Delta_{cross-range}$; otherwise, range resolution is reduced due to foreshortening. The field of view (in sq. meters) is $A = L\Delta_{range} W\Delta_{cross-range}$ where L is the length (x dimension), and W is the width (y dimension) of the video frame (in pixels)

Length and width errors – Target length and width measurement errors are assumed to be uniformly distributed with zero mean and standard deviation $2\sqrt{\frac{1}{12}(\Delta_{range}^2 + \Delta_{cross-range}^2)}$.

Positional error covariance - The positional error variances in the range and cross-range directions are:

$$\sigma_{range}^2 = \sigma_{\phi}^2 r^2 / \sin^2\phi$$
$$\sigma_{cross-range}^2 = \sigma_{\phi}^2 r^2 \tag{20}$$

where σ_{ϕ}^2 is the variance of the aim angle (incidence angle) error. In geographic coordinates, the covariance matrix is rotated by the azimuth angle θ of the video platform relative to the target

$$\mathbf{M}_{geo} = \begin{bmatrix} \sigma_{range}^2 \cos^2\theta + \sigma_{cross-range}^2 \sin^2\theta & \sin\theta\cos\theta\sigma_{range}^2 - \sin\theta\cos\theta\sigma_{cross-range}^2 \\ \sin\theta\cos\theta\sigma_{range}^2 - \sin\theta\cos\theta\sigma_{cross-range}^2 & \sigma_{range}^2 \sin^2\theta + \sigma_{cross-range}^2 \cos^2\theta \end{bmatrix}. \tag{21}$$

Probability of detection and false alarm rate – Tables are used to define P_d as a function of range and incidence angle. N_{fa} is a constant, with the effective number of false alarms generated for a particular frame being AN_{fa}.

Probability of identification – The video sensor system is also assumed to have some capability (ATR or human operator) for identifying targets. Tables are also used to define the average P_{id} as a function of range and incidence angle.

HUMINT Model

We assume a human observer measuring range, R and azimuth angle θ (measured CW from true north) with respect to a known position reference. Parameters of the HUMINT sensor observation model specification file are listed in Table 8.

Table 8 MRS HUMINT sensor observation model specification file format

Field Name	Data Type	Enumeration
Range error (m)	float	≥ 0
Bearing error (radians)	float	≥ 0
Revisit time (sec)	integer	> 0
Revisit time distribution	string	{constant, exponential}
Pd vs. range table	string	filename
Pid vs. range table	string	filename
Observer locations file	string	filename

Positional error - The position of a point (x_0, y_0) in Cartesian coordinates relative to a reference can be computed from the measurements, viz.,

$$\begin{aligned} x_0 &= R_0 \sin\theta_0 \\ y_0 &= R_0 \cos\theta_0 \end{aligned} \tag{22}$$

The positional error covariance matrix is:

$$\begin{bmatrix} \sigma_R^2 \sin^2\theta + R_0^2\sigma_\theta^2 \cos^2\theta & \frac{1}{2}(\sigma_R^2 - R_0^2\sigma_\theta^2)\sin 2\theta \\ \frac{1}{2}(\sigma_R^2 - R_0^2\sigma_\theta^2)\sin 2\theta & \sigma_R^2 \cos^2\theta + R_0^2\sigma_\theta^2 \sin^2\theta \end{bmatrix} \tag{23}$$

where σ_R^2 is the range measurement error variance and σ_θ^2 is the angle measurement error variance.

Probability of detection and false alarm rate –P_d vs. range is defined in a table which characterizes human performance is detecting targets as a function of range. N_{fa} is assumed to be zero.

Probability of identification – P_{id} vs. range is also defined in a table which characterizes human performance is identifying targets as a function of range.

Report Format

Table 9 shows the current MRS output report file format. If a sensor is not used those fields have the value “Unused”.

Table 9 MRS output file format

Column Number	Field	Description	Data Type	Enumeration	Example
1	Sensor	Type of sensor	string	{GMTI, UGS, SIGINT, video, HUMINT, IMINT}	IMINT
2	Sensor-ID	Instance of one of these sensors	string		EO
3,4	Sensor-X-Y-Pos.	X-Y location of sensor platform	float,float		100121, 90010
5	Time (sec,)	Elapsed time of report	integer	≥ 0	110
6,7	Tgt-X-Y Position (meters)	East-west, north-south location of report w.r.t origin of scenario area	float,float		1180, 5480
8,9,10	Tgt-2x2 Covar. (meters)	Elements c11, c12, and c22 of 2x2 positional covariance	float,float,float		100, 40, 200
11	Radial velocity (m/sec)	Radial velocity w.r.t. look direction of the radar	float	≥ 0	3.6
12	ID	One of N pre-defined ground targets	string	{T-72, BMP-1, BRDM-2 BTR-60, MAZ-543, MT-LBU, M1035A2, GAZ-66, ZIL-131, SA-8}	T-72
13	Pid	Probability of correct identification	float	[0,1]	0.9

14	Wheeled-tracked	Does the vehicle have wheels or tracks?	string	{tracked, wheeled, other}	tracked
15	Wheeled-tracked-Pcc	Probability of correct classification of track-wheel feature	float	[0,1]	0.6
16	Heavy-light	Is the vehicle heavy or light?	string	{heavy, light, other}	heavy
17	Heavy-light-Pcc	Pcc of track-wheel feature	float	[0,1]	0.6
18	Rpm	Engine RPM	string	{2000, 2100, 2600, 3200, 3400, 3600, other}	2100
19	Rpm-Pcc	Pcc of RPM feature	float	[0,1]	0.6
20	No. cylinders	Number of engine cylinders	string	{6, 8, 12, other}	8
21	No. cylinders-Pcc	Pcc of N-cylinders feature	float	[0,1]	0.6
22	No. axles	Number of axles	string	{2, 3, 4, 6, 8, other}	3
23	No. axles-Pcc	Pcc of N- axles feature	float	[0,1]	0.6
24	Length (meters)	Length of detected region	float	> 0	4.6
25	Length-error	Length measurement error	float	≥ 0	0.5
26	Width (meters)	Width of detected region	float	> 0	2.3
27	Width-error	Width measurement error	float	≥ 0	0.5
28	Pd	Probability of detection	float	[0,1]	0.9
29	Nfa	Number of false alarms per sq. km.	float	≥ 0	1.4
30	Emitter Freq. (Mhz)	Emitter frequency	float	> 0	33
31	Emitter Power (watts)	Emitter power	float	> 0	2
32	PRF (per sec.)	Pulse repetition frequency	float	≥ 0	0
33,34	G.t.X-Y-Pos. (meters)	Ground truth x-y location	float,float		1331, 202
35	G.t. ID	One of N pre-defined ground targets	string	{T-72, BMP-1, BRDM-2 BTR-60, MAZ-543, MT-LBU, M1035A2, GAZ-66, ZIL-131, SA-8}	T-72
36	G.t. UID	Unique identifier in cases of multiple instances of the same target ID	string		T-72_1

MRS Example

Consider a scenario (Fig. 3) in which one group of red forces (top arrow) leave a garrison and move into offensive positions (circle in the northeast), followed by a second group a short time later (bottom arrow). As part of this scenario, we used MRS to simulate the movement of 19 vehicles over a one hour period with the following sensors: GMTI (located south and east of the playbox), 4 sets of UGS, video, SIGINT, HUMINT (2 observers), and IMINT (SAR). Figs. 4 and 5 show the ground vehicle tracks, and sensor locations/flight paths. Roughly 18,700 ground truth entries were generated (1 sec. sample time). For the two GMTI sensors operating at an average revisit rate of 10 sec., about 3900 reports were generated with N_{fa} = 0.01/sq. km. and a considerable amount of terrain obscuration in the deployment area (Fig. 5). About 44 HUMINT reports were generated by two observers, 80 IMINT reports from one SAR image near the end of the scenario, 300 SIGINT reports, 4700 UGS reports from the four groups of sensors, and 1000 video reports.

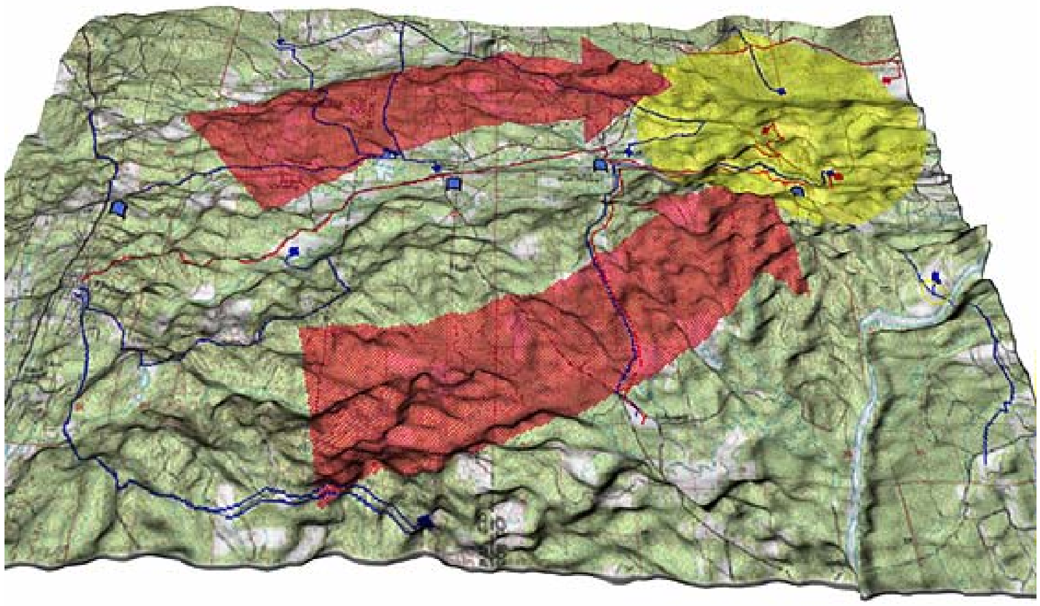

Fig. 3 Example scenario. Playbox is approximately 620 sq. km. in area

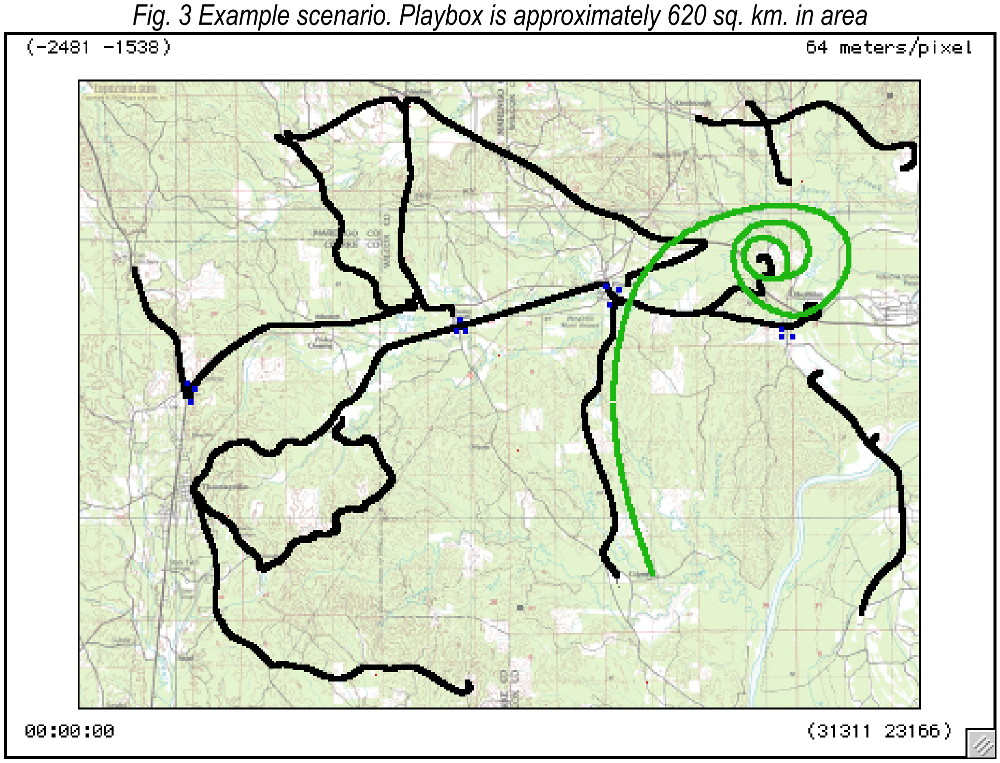

Fig. 4 MRS spatial display showing ground tracks (black), UGS locations (blue), HUMINT observers (gray), and video track (green).

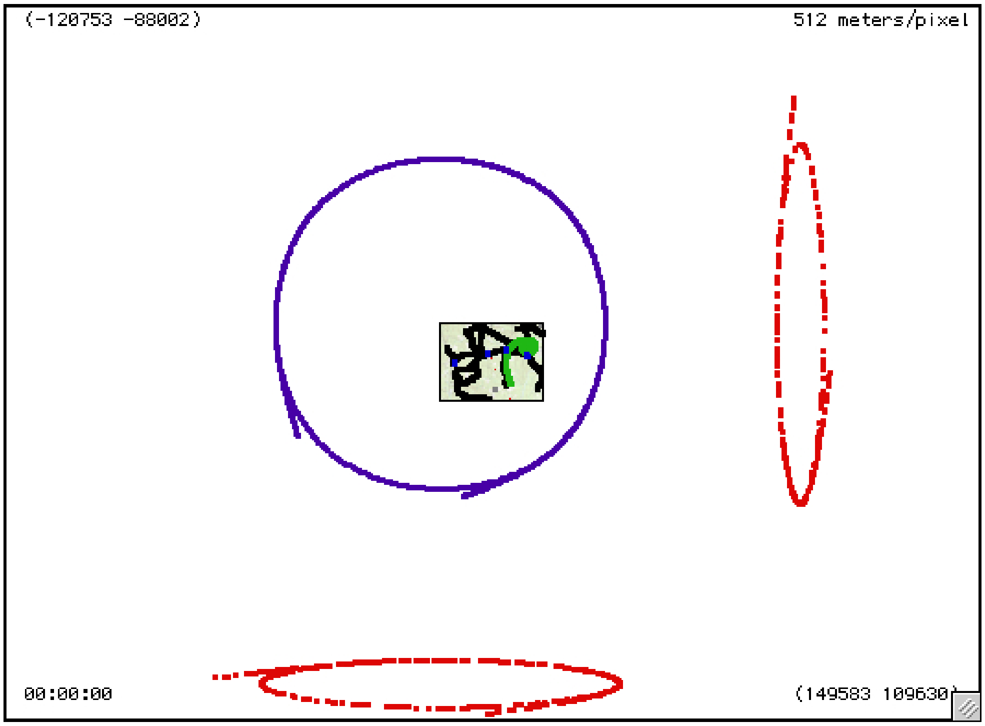

Fig. 5 MRS display zoomed out 8x showing SIGINT (purple) and GMTI (red) surveillance orbits.

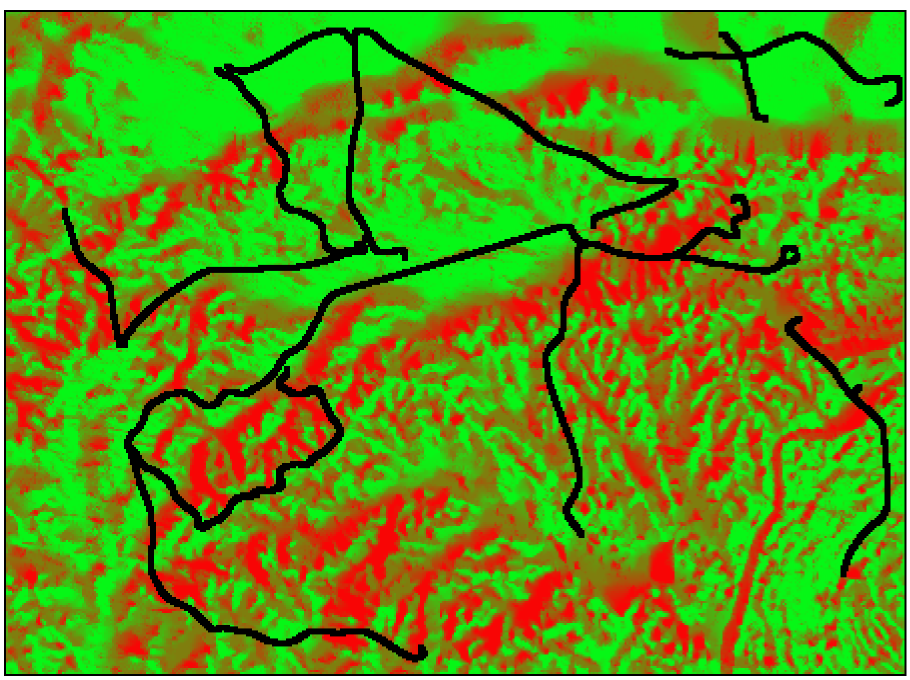

Fig. 5 Ground vehicle tracks overlaid on observability map where P_d = 0 (red) and P_d = 1 (green).

Summary

MRS is a software tool for generating simulated multisensor contact reports and ground truth. It contains a spatial editor for creating ground tracks along which vehicles move over the terrain. Vehicles can start, stop, speed up, or slow down. The spatial editor is also used to define the locations of fixed sensors such as UGS and HUMINT observers on the ground, and flight paths of GMTI, IMINT, SIGINT, and video sensors in the air. Contact reports provide measurements of a ground vehicle's location, observed features (e.g., size, shape, speed, emissions, etc.), and classification/ID (as produced by an upstream ATR algorithm). They also include estimates of the associated measurement errors and detection/classification performance of the sensors and their associated exploitation processes for use by downstream tracking/fusion algorithms. MRS supports generic GMTI, HUMINT, IMINT, SIGINT, UGS, and video sensors. Outputs are in the form of flat files (ASCII text) which can be easily imported into most tracking/fusion applications.

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