GMTI Tracking Improved by 18 dB using Cognitive Algorithm

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Abstract—Existing tracking algorithms face combinatorial complexity in heavy clutter. Their performance is limited by the number of computer operations, they do not extract all the information available in radar signals, and do not reach Cramer-Rao performance bounds. A cognitively inspired algorithm was developed and applied for improved tracking. Models for GMTI tracks have been developed as well as cognitive architecture incorporating these models. The cognitive tracker overcomes combinatorial complexity of tracking in highly-cluttered scenarios; its performance achieves Cramer-Rao Bounds and results in about 20 dB (two orders of magnitude) improvement in signal-to-clutter ratio.

I. DEFFICIENCY OF EXISTING METODS

When signals are week, below clutter, detection and tracking is difficult [1]. Performance of existing algorithms is significantly below the information-theoretic limits indicated by the Cramer-Rao Bound for tracking [2]. Existing algorithms operate in a two-step process. First, Doppler peaks are detected. Second, these peaks are used to initiate tracks. The performance of this procedure is limited by computational complexity of track initiation. If the threshold is reduced, the number of detected peaks grows quickly. Faster computers do not solve the problem because the processing requirements are combinatorial in terms of the number of peaks, so that a tenfold increase in the number of peaks results in a million fold increase in the required computer power. Thus limitations of existing tracking algorithms are due to combinatorial complexity (CC) of computations and not the absence of information in the data.

The number of combinations quickly grows with the number of objects and conditions; say, a medium complexity problem of recognizing *100* different objects in various combinations might lead to a need to learn 100^{100} combinations; this number is larger than the number of all interactions in the entire life of the Universe [3].

II. COGNITIVE ALGORITHM FOR GMTI TRACKING

Cognitively inspired algorithm, neural modeling fields NMF [4] eliminated CC by using a dynamic logic process “from vague to crisp” as described below. The presentation will discuss experimental cognitive foundations for this process. In NMF each input neuron, $n = 1,\dots N$, encodes four values: range and cross-range positions of cell n (x_n, y_n), amplitude (RCS), and

Doppler (a_n, D_n): $\boldsymbol{X}(n) = (x_n, y_n, a_n, D_n)$. Signals $\boldsymbol{X}(n)$ form a set that we call an input neural field, or in cognitive terminology, a set of bottom-up signals. Priming or top-down signals to these neurons are generated by models, $\boldsymbol{M}_h(S_h,n)$, $h = 1,\ldots H$. Each model is characterized by its parameters, S_h. We consider targets moving with constant velocities, (vx_h, vy_h):

$$\boldsymbol{M}_h(S_h,n) = (x0_h + vx_h\, t_n, y0_h + vy_h\, t_n, a_h, D_h) \tag{1}$$

Neural weights specify interactions between bottom-up and top-down signals. To define neural weights, we compute first similarity measures, ℓ, between bottom-up signals $\boldsymbol{X}(n)$ and top-down signals $\boldsymbol{M}_h$, and then compute weights:

$$\ell(\mathrm{n}|\mathrm{h}) = (2\pi)^{-2}(\det \mathrm{C_h})^{-0.5} \cdot \exp\{-0.5\,(\mathbf{X}(\mathrm{n}) - \mathbf{M}_\mathrm{h}{}^{\mathrm{T}})\mathrm{C_h}^{-1}\,(\mathbf{X}(\mathrm{n}) - \mathbf{M}_\mathrm{h})\}. \tag{2}$$

$$f(h|n) = r(h)\,\ell(n|h) / \sum_{h' \in H} r(h')\,\ell(n|h'). \tag{3}$$

Parameters $r(h)$ are the relative numbers of radar returns associated with model h. For moving object models we assume that a single radar return is received from each scan; this is compatible with a low setting of threshold for radar signal detections. The number of radar scans, k, is known, therefore, $r(h) = k$ are known quantities. We denote the clutter model by $h = 1$, it is characterized by average amplitude, Doppler, and rate,

$$M_1(S_1,n) = (a_1, D_1), \quad r(1) = (N - H\,k)/N, \tag{4}$$

The cognitive algorithm NMF is an iterative process [8], it start with an initial guess of model parameters. Next, the algorithm computes neural weights (3), then new values of the model parameters. Model parameter equations are written using the following notation for a standard neural operation of computing a weighted sum,

$$<\ldots>_h = \sum_{n \in N} f(h|n)\,(\ldots)_n. \tag{5}$$

Model parameters are computed at each iteration as follows

$$a_h = < a_n >_h. \tag{6}$$

$$\begin{aligned} &y0_h < 1 >_h + vy_h < t_n >_h = < y_n >_h, \\ &y0_h < t_n >_h + vy_h < t_n^2 >_h = < y_n\, t_n >_h. \end{aligned} \tag{7}$$

$$\begin{aligned} &x0_h < 1 >_h + vx_h < t_n >_h = < x_n >_h, \\ &x0_h < t_n >_h + vx_h\,(< t_n^2 >_h + c < 1 >) = < x_n\, t_n >_h + c < D_n >_h. \end{aligned} \tag{8}$$

Here, $c = \sigma x_h^{\ 2} ./\sigma D_h^{\ 2}$. After parameters are computed as above, standard deviations are computed, as follows:

$$\sigma = \sigma_{initial} \, exp\{-7\ i\ /\ IT\ \} + \sigma_{final}. \qquad (9)$$

Here, $\sigma_{initial}$ and σ_{final} are initial and final values of standard deviation. The initial value is defined using standard statistical procedure [5] from all available data. The final value is defined by the radar measurement errors. The presentation will describe the final detection procedure. The cognitive tracking algorithm computational complexity is proportional to the number of data points and the number of tracks, *const*N*H.* This number is linear in *N* and in *H*, rather than combinatorial, $\sim H^N$ like in MHT.

III. TRACKING EXAMPLE

An application example of the cognitive tracker is illustrated Fig. 1. Fig. 1(a) shows true track positions in a 0.5km * 0.5km data set, while Fig. 1(b) shows the actual data available for detection and tracking. In this data, the target returns are buried in the clutter, with signal-to-clutter ratio of about –2dB for amplitude and –3dB for Doppler. Here, the data is displayed such that all six revisit scans are shown superimposed in the 0.5km * 0.5km area, *500* pre-detected signals per scan, and the brightness of each data sample is proportional to its measured Doppler value. Figs. 1(c)-1(h) illustrate the evolution of the models. Fig. 1(c) shows the initial vague-models, while Fig. 1(h) shows the model upon convergence at *20* iterations. Between (c) and (h) the algorithm automatically decides how many models are needed to fit the data, and simultaneously adapts the model parameters. In (c) and (d), the algorithm fits the data with one model, and uncertainty is somewhat reduced. Between (d) and (e) NMF uses more than one track-model and decides that it needs two models to 'understand' the content of the data. Fitting with *2* tracks continues until (f); between (f) and (g) a third track is added. Iterations stop at (h), when similarity stops increasing. Detected tracks closely correspond to the truth (a).

Target signals are below clutter in this example,. A single scan does not contain enough information for detection. Detection should be performed concurrently with tracking, using several radar scans, and six scans are used. In this case, a standard multiple hypothesis tracking [6], evaluating all tracking association hypothesis, would require about 10^{1500}, a number too large for computation. Therefore, tracking requires strong signals, with about a 15 db signal-to-clutter ratio [1]. The cognitive tracker successfully detected and tracked all three targets and required only 10^6 operations, achieving about 18 dB improvement in signal-to-clutter sensitivity.

Recent neuroimaging experiments [7] proved that visual perception in the human brain works according to the dynamics of the algorithm described in this paper, in the process "from vague to crisp."

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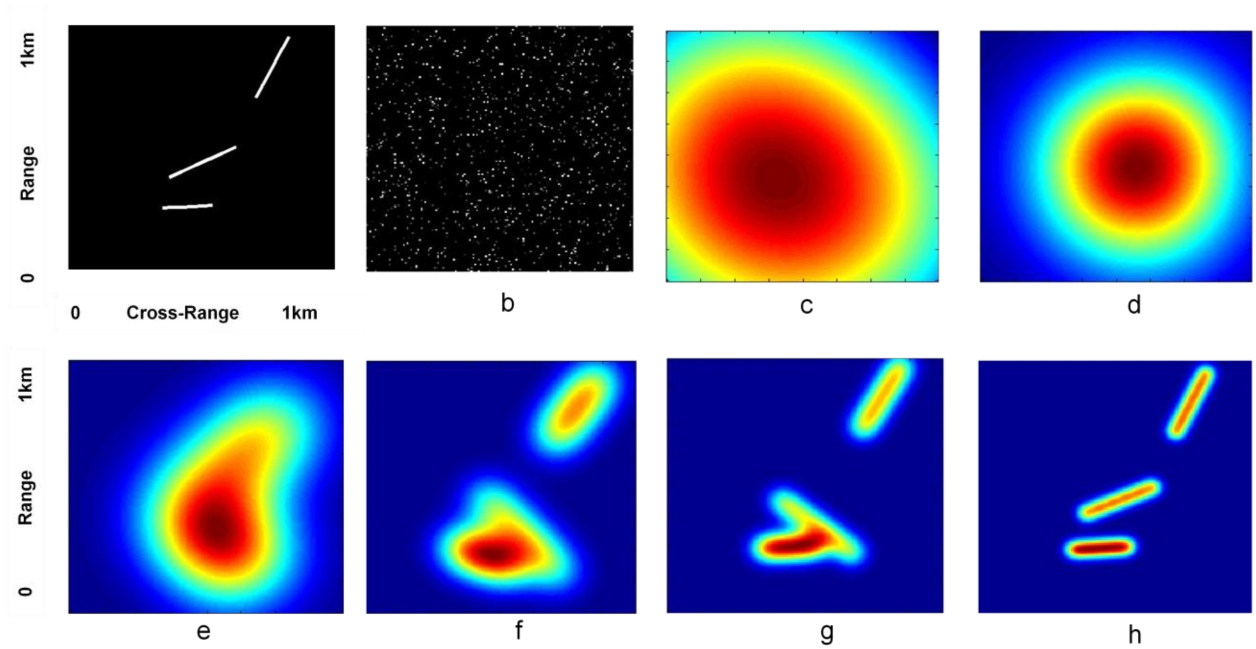

Fig. 1. Detection and tracking objects below clutter using cognitive tracking algorithm.

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