Brainlike Monitoring for Shallow Water Attack Prevention

Brainlike, Inc.
January, 2012

Overview

Developing, delivering, and managing defense and homeland security surveillance systems carries many challenges. Brainlike, Inc. delivers unique, proven technology to meet them. Shallow water attack monitoring and prevention (SWAMP) is a case in point that will be highlighted in this report.

The solutions Brainlike offers to related problems fall into two categories. The company offers a real-time monitoring process, which automatically converts hard-to-interpret sensor information into easy-to-manage form. The company also offers a closely related development framework, which greatly simplifies and speeds product delivery.

Both the Brainlike monitoring process and the Brainlike development framework capitalize on a basic but essential ability found in the simplest animals: the capacity to update analytical information *during* sensing and information processing. What makes this capacity so valuable in animals is their ability to do it automatically, continuously, efficiently, and effectively. The company calls its own version of this capacity "Brainlike auto-adaptivity," and offers it as an extremely valuable and efficient computing counterpart to primitive animal learning.

An Example

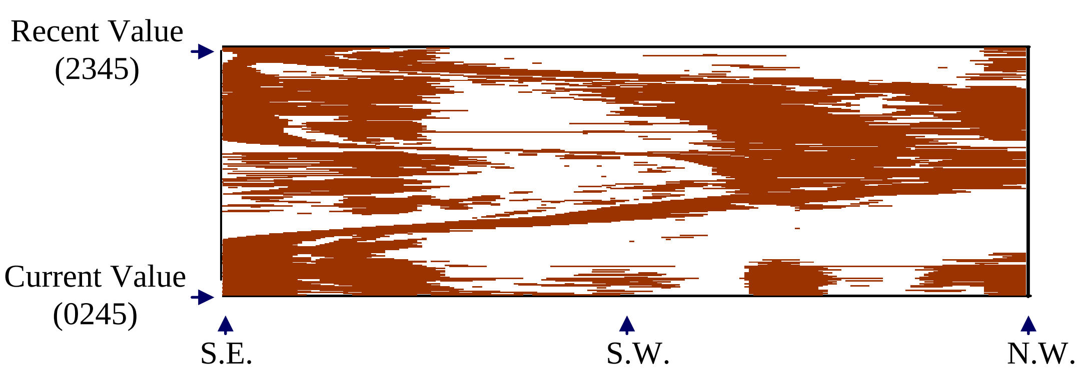

Figure A1. Transient Data Without Brainlike Learning

To demonstrate the added value of Brainlike technology for shallow water intrusion, a sonar test dataset for monitoring San Diego harbor shipping activity was analyzed. SPAWAR Systems Center Pacific, with support by the Office of Naval Research, produced the raw data, and James Wilson from Neptune Sciences, Inc. kindly provided a dataset that was suitably pre-processed by his QuIPS system for this illustration.

Figures A1 and A2 illustrate Brainlike transient detection sensitivity. Figure A1 shows sonar output over a three hour period of activity. The figure is a pixel array with 540 rows and 181 columns. Each row in the figure corresponds to a 20 second time period, and each column corresponds to a relative bearing degree. Each pixel represents a sonar signal from a passive, broadband array, pointing out of San Diego Harbor. Each such pixel is shown as a red mark if a fixed cutoff value was exceeded and shown as a white mark otherwise. The figure shows routine harbor shipping traffic, appearing as bands of red moving down from either left to right or right to left as ships enter the harbor.

In addition to normal shipping activity, the Figure A1 dataset includes 10 blips that were inserted to simulate transient activity from an intruding mini-submarine. The red versus white cutoff value for Figure A1 was selected to show these transient blips as clearly as possible.

Figure A2 illustrates the same scenario as in Figure A1, except the pixels shown in Figure A2 are output values from the Brainlike monitoring process. Each pixel shown in Figure A2 measures how unexpected its corresponding Figure A1 pixel was, relative to what the Brainlike process had learned to expect for that pixel up to that time point. For example, the 10 circled blips in the center of the figure represent the transients that were included to simulate intrusive activity.

The Brainlike process identified the 10 circled blips in Figure A2 as unexpected because no surrounding activity at their corresponding time point or no recent prior activity had led the process to expect the transients to occur at that time. On the other hand, the Brainlike process identified very few of the other data points as unexpected. Reason: the Brainlike process quickly learned to expect that if sonar output signal levels had been substantial just prior to or close to any given pixel, then that pixel level would be substantial as well, therefore not unusual.

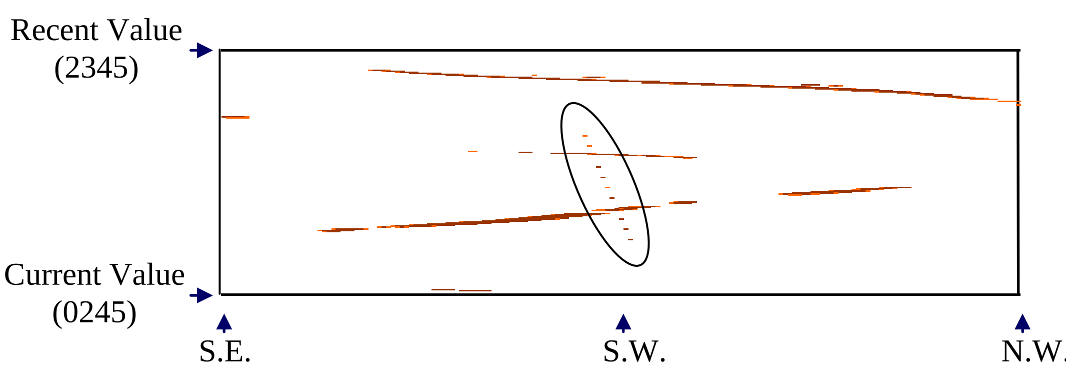

Figure A2. Transient Data With Brainlike Learning

The Brainlike process that produced the Figure A2 results was run in conjunction with a simulator. During the simulation, each set of 181 sonar array output values corresponding to the rows of Figure A2 were supplied as input values to the Brainlike detector, one row at a time, starting from the top row. At each time point corresponding to a row, the detector updated its learned parameters, starting with initial values that reflected no learning. At each time point the detector also computed 181 expected values based on what had been learned up to time point, compared actual values to expected values, and marked each pixel as either expected or unexpected accordingly.

Total Operating Cost Reduction Emphasis

Above all, Brainlike products and services are driven by a strong business case for reducing total operating costs. The company has developed and analyzed sophisticated cost analysis models for real-time surveillance systems. These models include metrics reflecting false alarm rates and costs, missed incident detection rates and costs, product development costs, and a variety of delivery process risk factors. The models point clearly toward two key ingredients that the company can provide for reducing total operating costs: (1) the capacity to adapt continuously *during* product development, delivery, and deployment; and (2) the capacity to do so automatically, without the need for human analytic intervention. Other cost factors include, but are not limited to, operator workload, data transmission, and data storage, all of which have been "dollarized" in Brainlike reports, which are available upon request.