Brainlike Video Data Reduction

Brainlike Inc., has been refining smart sensing methods to reduce clutter in real time on unmanned aircraft sensors. Smart sensing removes camera image clutter, such as clouds, white caps, glint, and camera lens imperfections, allowing features of interest such as ship or marine mammal wakes to show up clearly. Brainlike sensing removes clutter by continuously learning expected clutter metrics under novel and changing conditions, making event detection robust. Doing so allows small pixel windows containing events of interest to be identified accurately and in real time. As a result, only such windows will be transmitted, telemetry will be reduced, less energy will be used, and small, unmanned aircraft persistence will be increased.

In order to operate in real time, Brainlike sensing must operate quickly. For example, suppose that cloud masking requires features to be extracted from 10 by 10 windows within 4,000 by 3,000 camera images, being produced at a rate 20 frames per second. In order to learn continuously in this case, Brainlike sensing must handle nearly 240 million windows per second for each feature. Processing must include computing the feature values and updating their expected values. Further, in order to operate on small, unmanned vehicles, Brainlike sensing must use very little energy. The capacity to operate quickly, efficiently, and adaptively distinguishes the Brainlike process from others.

Brainlike sensing identifies and removes cloud cover and other clutter in images, by passing small windows over each image in real time. Each window covers an image section, having a configurable size in time and space. For each window feature, Brainlike sensing continuously updates its expected value and a corresponding deviance value. Each expected value may be computed as either a simple mean or a function of nearest neighbors in time or space. The Brainlike sensing process adapts continuously by updating weights for estimating expected values, as well as deviance distribution metrics, recursively and in real time. In so doing, the process can flag large sources of clutter, such as clouds; it can identify targets as having highly deviant values; and it can impute small sources of clutter such as the white cap specks shown in Figure 1. As a result, operators or automated detection processes can readily identify and classify targets of interest. Because Brainlike sensing deviance values continuously adjust for changing conditions, cutoff values based on them detect and classify clutter robustly, from one frame to another.

Brainlike windows may also include homologous pixels from recent images. For example, each window could be made up of 10 by 10 by 5 pixels that include 10 by 10 windows from the current frame, along with homologous 10 by 10 windows from the four previous frames. Pixels from each such window could be used to compute several feature values, such as edge and other wake-specific values. Windows computed in this way could identify wakes caused by either broaching mammals or periscopes as unexpected pixel changes. Meanwhile, Brainlike sensing could learn to expect other changes over time and space, such as white cap formation, as functions of nearest neighbor pixels in time or space that occur predictably from one window to another.

Figure 1 shows one of several camera images that Brainlike, Inc., analyzed in a case study, under contract with the Office of Naval Research. A time series consisting of many such images was captured at a rate of eight per second from a camera turret residing on an unmanned airborne vehicle (UAV). The turret contained six, slightly overlapping cameras. A GPS-based controller was used to register each image on the same ocean area. For this particular image, part of the frame was covered by only three different cameras on the turret. Each image was made up of 800 by 800 pixels, each having a 12-bit gray scale value. The black regions on both sides of the image were not covered by any of the cameras in the turret.

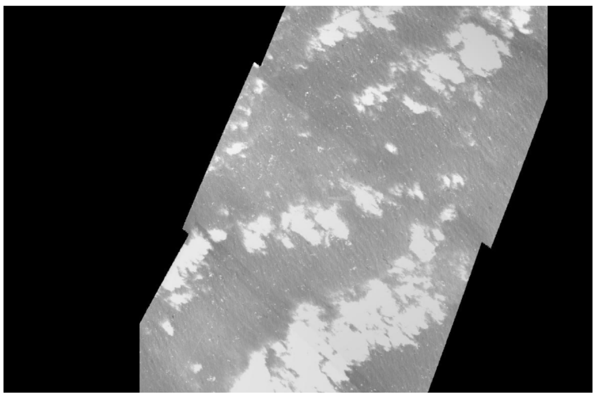

Figure 1. UAV Frame Sensor Data.

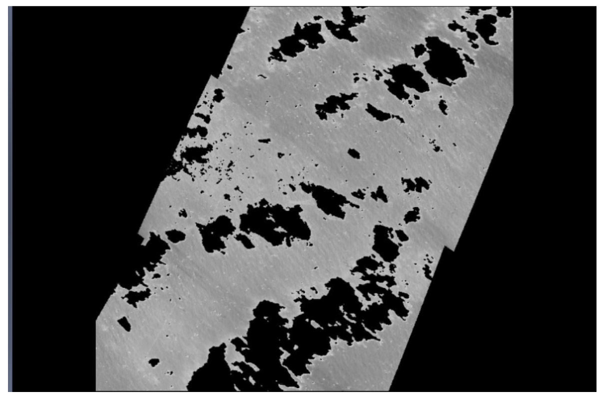

Figure 2. UAV Frame Masked Data.

In the Figure 1 case, a 10 by 10 window size was configured for cloud detection. Feature values were computed for each such window by summing its 100 values. A 5 by 5 window size was configured for whitecap detection. Feature values were computed for each such window by summing its 9 internal pixel values and subtracting its 16 external pixel values. For both cloud detection and whitecap detection windows, cutoff values were chosen that effectively and robustly distinguished clutter pixels from others in each frame. Figure 2 shows the resulting, masked counterpart to Figure 1.

Once clutter has been masked, events of interest, such as wakes from mammals or vessels, can be detected. For example, the Figure 1 image contains a simulated wake, which would be difficult to detect either automatically or visually, in the presence of unmasked clutter. However, the wake becomes much easier to detect once such clutter has been masked, by identifying masked windows containing white pixels. The location of the wake is shown in Figure 4, next to its corresponding unmasked image, shown in Figure 3.

Brainlike sensing results may be used either to simplify operator analysis or to reduce data upstream of telemetry, or both. For example, cloud coverage percentage could first be computed in real time for each processed image like the one shown in Figure 2, and then used to control transmission and presentation of each frame. Alternatively, averaging could be used to reduce transmitted data routinely, unless windows of interest are identified upstream of telemetry. If such windows are identified, they can be computed in full resolution. In addition, pale pixels like those shown in Figure 4 could be created and transmitted by averaging pixels in non-overlapping windows, covering nearest neighbor pixels in space and time. Transmission could either be triggered by windows exceeding Brainlike adaptive thresholds or the number of transmitted windows could be fixed. For example, two high thresold windows like the one shown in Figure 4 could be transmitted and presented persistently to operators during 20 consecutive frames in one second, along with one average value for each set nearest neighbor pixels in a 20 rows by 20 columns by 20 time slices box. Resulting data compression would be 727.72 to one (727.72 = [(640,000 pixels per frame)×(20 frames per second)]/[(2 transmitted windows per frame)×(20 ×20 pixels per window) ×(20 frames per second) + (640,000 pixels per frame) ×(20 frames per second)]/(20×20×20 pixels per average per second)]). If the two windows were transmitted once per second alone, without the averaged pixel data, resulting data compression would be 16,000 to one (16,000 = [640,000 pixels per frame ×20 frames per second]/[(2 transmitted windows per second)×(20 ×20 pixels per window)]). Data compression at such high levels could add substantial transmission value, especially when used along with other, established data compression methods.

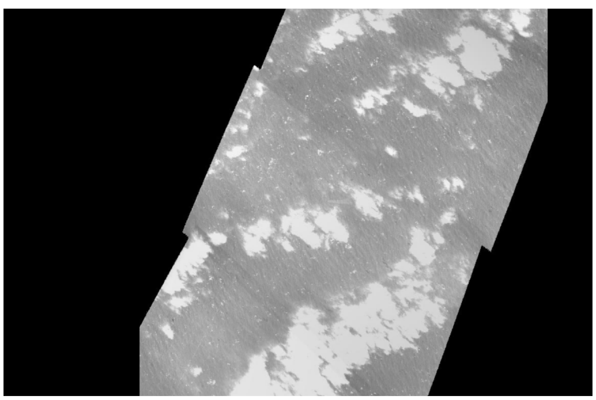

Figure 3. UAV Frame Sensor Data.

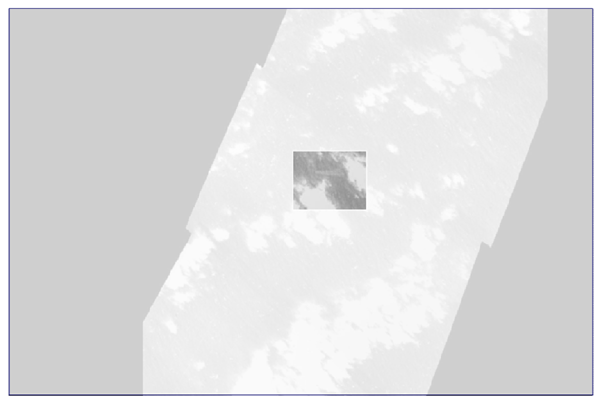

Figure 4. UAV Frame Reduced Data.

Beyond camera image processing, Brainlike sensing can be applied to any number of sensing operations, ranging from sonar-based clutter reduction and radar-based imbedded explosive device detection in military applications, to utility, environment, equipment, and health monitoring in commercial applications. In all such applications, Brainlike capacity to reduce data effectively, continuously, efficiently, and affordably, distinguishes it from available alternatives.

In summary, Brainlike sensing receives raw data in real time and reduces it to important information. When integrated with an unmanned aerial vehicle (UAV) camera system, Brainlike sensing can mask pixels containing clouds and other forms of clutter. Brainlike sensing can then identify events of interest such as wakes, effectively and in real time. Resulting benefits include reduced telemetry, increased remote sensor persistence, and more effective target recognition. Video film results, showing the effects of Brainlike processing for the case study in this report, are available from Brainlike Inc., upon request.