Image Analysis Based on Soft Computing and Applied on Space Shuttle Safety during the Liftoff Process.

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Imaging techniques based on Soft Computing (SC) and developed at Kennedy Space Center (KSC) have been implemented on a variety of prototype applications related to the safety operation of the Space Shuttle during the liftoff process. These SC-based prototype applications include detection and tracking of moving Foreign Objects Debris (FOD) during the Space Shuttle liftoff, visual anomaly detection on slidewires used in the emergency egress system for the Space Shuttle at the launch pad, and visual detection of distant birds approaching the Space Shuttle launch pad. This SC-based image analysis capability developed at KSC was also used to analyze images acquired during the accident of the Space Shuttle Columbia and estimate the trajectory and velocity of the foam that caused the accident.

1. INTRODUCTION

These imaging techniques adaptively perform image segmentation, edge extraction, and image enhancement using techniques developed at KSC and based on Fuzzy Reasoning (FR), one of the key components of SC. NASA has filed for patents on these techniques known as Fuzzy Reasoning Edge Detection (FRED), Fuzzy Reasoning Adaptive Threshold (FRAT), and Fuzzy Reasoning Image Enhancement for Binarization (FRIEB). NASA has also granted licenses of these FR-based

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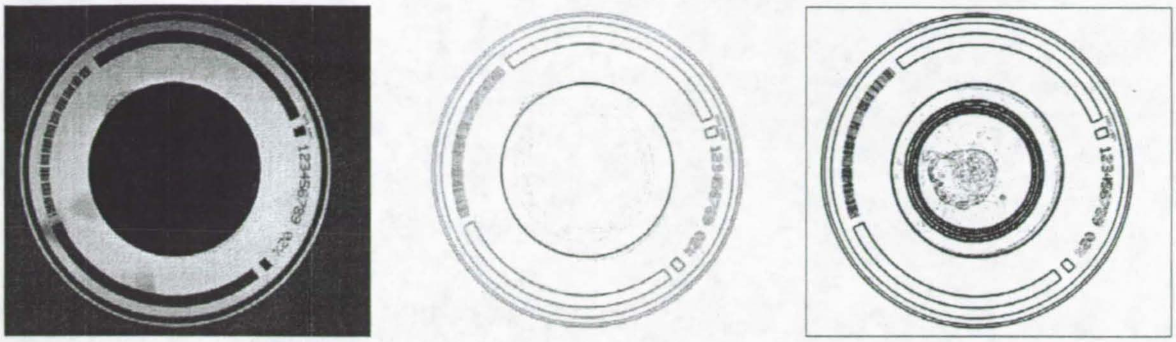
imaging techniques to companies from different fields, including surveillance, security screening, medical, text digitalization, and aerospace. Artificial Neural Network (ANN) and Genetic Algorithm (GA), two other key components of SC were also utilized to implement some of these prototype applications using commercially available ANN-GA software. The utilization of ANN and GA on image classification leads to valuable learning and optimization capabilities.

2. SOFT COMPUTER TECHNIQUES

2.1 Fuzzy Reasoning Edge Detection (FRED)

Edges carry the most important information in images and accurate edge detection is vital to perform advanced image processing and analysis. The problem of determining what is (and what is not) an edge is confused by the fact that edges are very often partially hidden or distorted by various effects, such as inadequate lighting and image acquisition noise. Fuzzy reasoning is a suitable framework for expressing heuristic processes applied to incomplete and imperfect data. FRED uses an odd-sided window of pixels to find the edge level of the pixel in the center of the window via fuzzy reasoning based on a heuristic analysis of four different intensity gradients of the two areas formed at both sides of the four diagonals (one vertical, one horizontal, one right-inclined, and one left-inclined) present in the window. A crisp edge value for the pixel in the center of the window is finally generated after a fuzzy membership function is evaluated using the optimal intensity gradient. FRED autonomously determines the size of the odd-sided window used to scan the image based on the size of the images; the smaller window size 3x3, is set for very low resolution images while window sizes as high as 21x21 are set for high-resolution images. Figure 1 shows an image of a CD having faint scratches on the center and the edge extraction of this image using FRED and Sobel, a technique widely used for edge detection.



Original Sobel FRED

Figure 1. Sobel and FRED methods applied to an image containing a CD with a defect in the center.

Figure 1 shows clearly that FRED exceeds Sobel's performance. FRED algorithm distinctly detects these faint scratches while Sobel fails to detect them. Numbers and marks on the CD are much more evident when FRED is used.

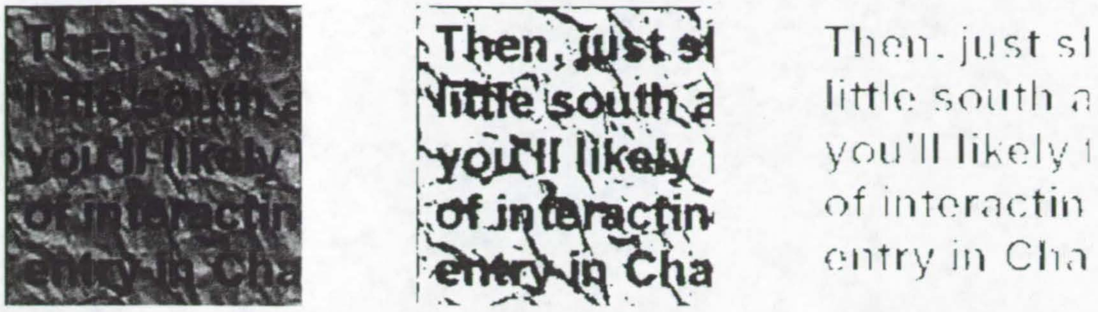
2.2 Fuzzy Reasoning Adaptive Thresholding (FRAT)

Binary image processing is of special interest because an image with binary format can be processed with very fast logical (Boolean) operators. Since most image display systems and software assume images of 8 or more bits per pixel, the binarization of these images usually takes 2 extreme gray tones, black and white, which are ordinarily represented by 0 or 255, respectively, in an 8-bit gray-scale display environment.

Usually a binary image is obtained from an 8-bit gray-level image by thresholding and assigning the low binary (0) and high (255) values to all gray levels based on the chosen threshold. Obviously, the threshold that is chosen has a critical importance since it controls the binary-based pattern classification that is obtained from the gray-level image. The key issue is to choose an optimal threshold so that the number of misclassified image pixels is kept as low as possible.

In FRAT, the image is considered as an array of singletons corresponding to image pixels, each having a membership value associated with a property of the pixel, the grayness level. For image thresholding, the membership function is defined in terms of the grade of pixel's grayness belonging to one of the two classes, background and foreground. The membership function is calculated via a triangular function at each of the two classes (background and foreground); the triangular function in each of the two classes is built using the average image grayness and histogram-based weight values at each class. In each of the two classes, the membership value (equal to 1) is the largest at the class average gray level and reduces its value when the difference between the pixel gray level and its class average level increases. This means that pixels with gray levels close to their corresponding class average gray levels have less fuzziness or ambiguity and thus can be classified with greater confidence than pixels with gray levels far from their class gray levels. The image entropy measure is used as a cost function to find the optimal threshold. The entropy factor needed to compute the entropy measure is calculated using a simple and fast computational linear function.

FRAT uses a similar but more efficient and faster computational approach than the one used in Huang-Wang method. Huang-Wang method uses a symmetric membership function, while the proposed approach uses a more realistic membership function having the highest and lowest gray levels holding nonzero histogram values as the domain limits. Huang-Wang method also limits the membership values within a range of 0.5 to 1.0 since it uses Shanon's entropy function as a cost function. FRAT uses a straight-line cost function that requires much less computational power than the Shannon function used by Huang-Wang method. Figure 2 shows the binarization of an image of



Original

Huang-Wang method
Threshold: 89
CPU time: 10.8 ms

FRAT method
Threshold: 8
CPU time: 2.5 ms

Figure 2. Huang-Wang and FRAT applied to an image containing a text with a corrupted background.

a text having a corrupted and noisy background; from figure 2, it is clear that FRAT determines a better optimal threshold (8) than Huang-Wang (89); FRAT takes less execution time, 2.5 ms compared with 10.8 ms. Image thresholding is the simplest image segmentation approach. It is actually a pattern classification procedure in which only one input feature is involved, the pixel intensity value. The key issue here is to automatically choose an optimal threshold value so that the number of misclassified image pixels is kept as low as possible.

2.3 Fuzzy Reasoning Image Enhancement for Binarization (FRIEB)

One of the key goals of performing binarization of grayed-scaled images is to be able to digitize text and numbers contained in the grayed-scale image acquired outdoors having uncontrolled image acquisition conditions (lighting, camera/video stabilization, etc.). These conditions degrade the ending quality of the acquired gray-scaled image making more difficult to binarize the text and numbers contained in the image; for example, the binarization and final digitization of car's tag numbers face these problems making them unfeasible or unreliable. FRIEB uses fuzzy reasoning based on heuristic techniques that compare the intensity value of each pixel in the image with the intensity levels of the immediate neighbors and decide if the intensity value of the pixel needs to be reduced or increased. Figure 3 shows the results of enhancing a text image via FRIEB prior to its

Figure 3. Effect of enhancing an image via FRIEB prior to binarization via FRAT and Huang-Wang techniques.

binarization via adaptive binarization methods, such as FRAT and Huang-Wang methods. In figure 3 the original image has a dark area on the right side of the image (due to uneven lighting distribution) that leads to poor binarization results using FRAT and Huang-Wang methods blocking the text located at the right side of the image. When the image is previously enhanced via FRIEB, the binarization of the image is dramatically enhanced as shown in figure 3.

2.4 Artificial Neural Network (ANN) and Genetic Algorithm (GA) Systems

ANN provides learning capabilities, and GA approach leads to robust learning results. The ANN scheme used along with FRED, FRAT, and FRIEB to add learning capabilities is commercially available (NeuroShell from Ward Systems Group, Inc.) and based on Probabilistic Neural Nets (PNN) formulated a little differently than conventional PNN; it is based on GA as opposed to a network structure. PNN's instantly trained, unlike back propagation. In fact, they do not really train at all; they memorize, and the only freedom they have to generalize is to vary the smoothing factors. So the approach used in NeuroShell memorizes all of the patterns in the training set. Then it begins generating genetic individuals with GA. Each individual is a set of smoothing factors, which, when applied to PNN, makes a complete net. That net is tested against the test set, and the results become the GA fitness function. The GA generates the smoothing factors that perform the best against the test set, but all nets thus generated by the GA are trained on the training set (memorized). NeuroShell Classifier contains this new GA-PNN network paradigm. NeuroShell Classifier is spawned via DLL functions to perform training and firing of the GA-PNN classification net.

3 PROTOTYPE APPLICATIONS

3.1 Detection and Tracking of Moving Foreign Object Debris (FOD) within a Complex Background.

A visual system for detecting and tracking multiple moving objects within a complex image background was developed and tested to detect potential FODs during the Space Shuttle liftoff. Images acquired and taped by a camera currently mounted at the Shuttle launch pad were used to test this real-time moving object detection and tracking system.

The system was able to detect and completely track two potential FOD's, as well as differentiate them from another moving object, such as ice flakes normally present during the Shuttle's liftoff. The detection and tracking algorithm relies fundamentally on FRAT and a novel motion analysis on consecutive images. In contrast with existing moving object detection approaches, the FRAT-based object detection technique does not need image subtraction between consecutive image frames to detect moving objects.

In the detection and tracking of moving FOD's during the Space Shuttle liftoff, this prototype system uses FRAT to binarize the image and generate binary blobs that represent the detected objects in each image frame. Further analysis of the blobs on consecutives image frames allows the system to determine which blobs/objects are moving following a consistent path. The image background during the Space Shuttle liftoff is quite complex as moving objects that are not FOD's (ice flakes, fume clouds, etc.) constantly appear at the scene following erratic moving paths.

Figure 4a shows a FOD (indicated with a blue circle) that seems to be a screw falling from the top left (close to the Space Shuttle's engine exhaust) toward the bottom left (close to the Space Shuttle's stabilizer tail). The image background shown in this figure is quite complex as lots of additional moving objects that seem to be ice flakes produced during the disconnection of the Space Shuttle's umbilical are constantly present as the FOD (screw) falls.

Figure 4b shows a second object (indicated with a blue circle) falling from the top center (close to the Shuttle's engine exhaust) toward the bottom left (close to the Shuttle's stabilizer tail). Figure 4c shows the complete paths of both objects detected and tracked by the system in real time.

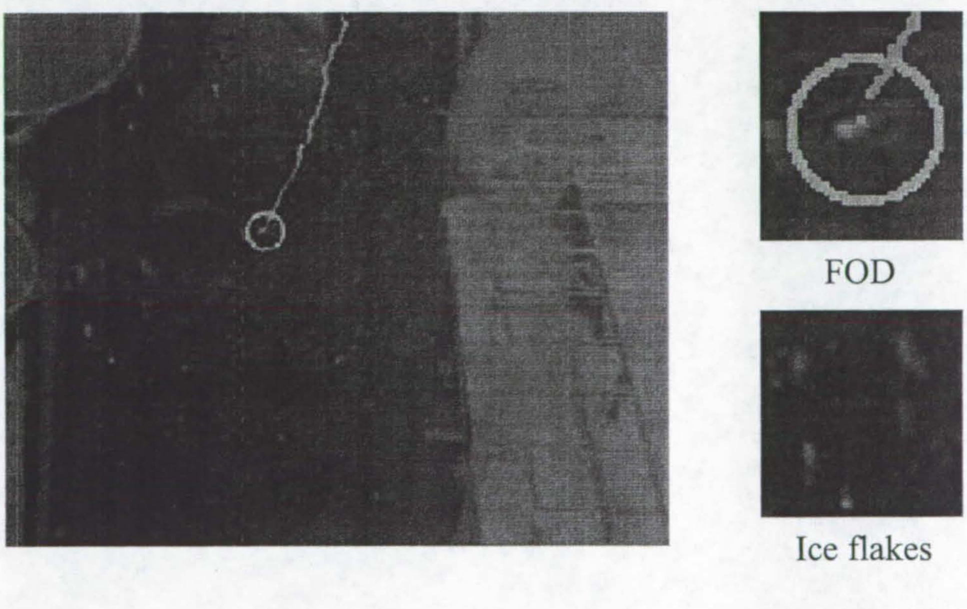


Figure 4a. Detection and tracking of first FOD.

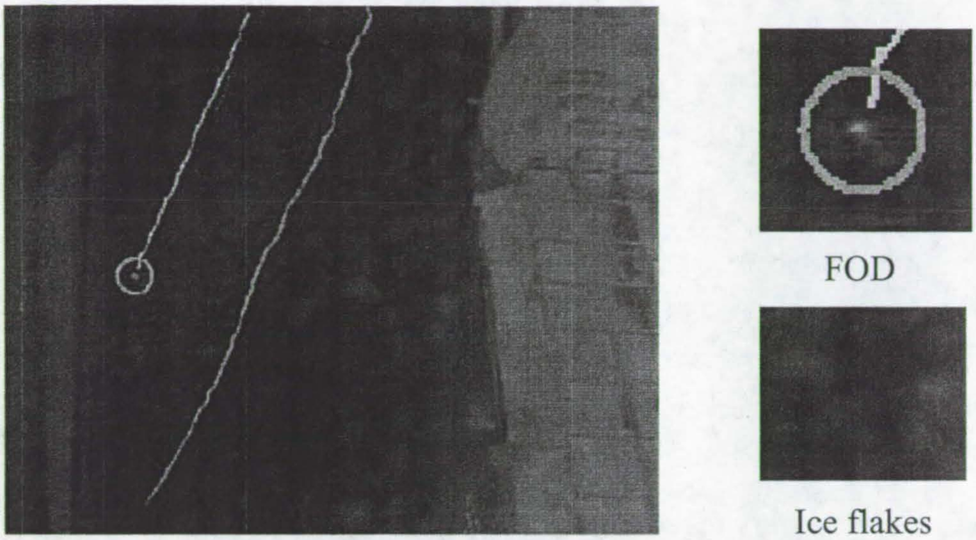


Figure 4b. Detection and tracking of second FOD.

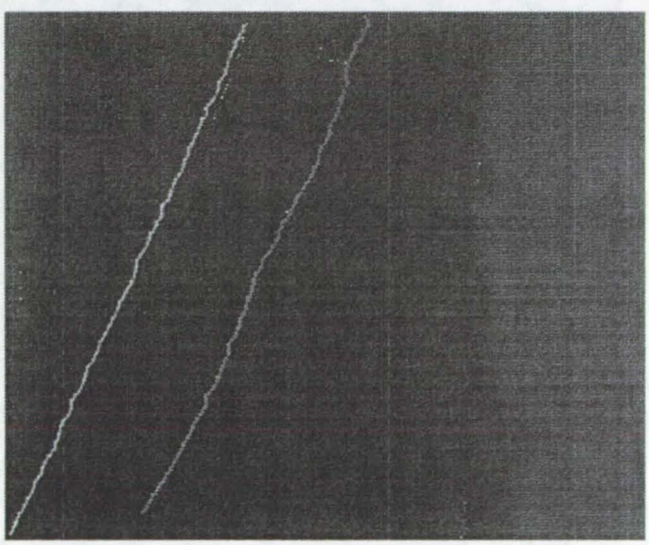


Figure 4c. Detection and tracking of both FODs.

The FR-based system was able not only to detect actual FOD's but also keep close track of them. The system was also able to process and execute motion detection features on every one of the 30 frames per second generated by the image acquisition system. This SC-based visual system prototype received Honorable Mention during the 2003 NASA Software of the Year Competition.

3.2 Visual Anomaly Detection on Slidewires

A prototype application was developed to determine the feasibility of detecting anomalies via SC on slidewires used at the emergency egress system located at the NASA Space Shuttle launch pad. The visual anomaly detection approach was tested by detecting loose strands, a common and sometimes hidden and hard-to-detect anomaly class on slidewires.

There are two Space Shuttle pads at KSC, each one having seven 1000-foot-long slidewires utilized to slide baskets that are used by the astronauts to evacuate the Space Shuttle launch pad in an emergency. Figure 5 shows astronauts drilling the emergency egress system at KSC; baskets are used to evacuate astronauts from the pad by sliding the baskets along the slidewires.

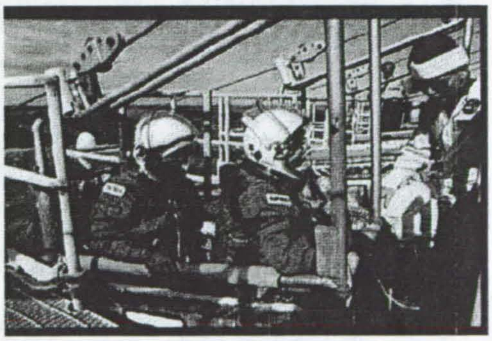


Figure 5. Astronauts drilling the emergency egress system at the Space Shuttle launch pad.

NASA built an inspection mechanism prototype called Cable and Line Inspection Mechanism (CLIM) equipped with four monochrome cameras to acquire images in four different angles along the slidewires. Figure 6 shows CLIM prototype being tested at the lab and the Space Shuttle launch pad. CLIM facilitates the visual inspection of the slidewires but still requires an operator to watch slidewire video images for many hours to spot and record anomalies. To eliminate human intervention that is prone to fail spotting and recording anomalies due to the tedious and repetitive nature of the job, an automated visual anomaly-detection system prototype was proposed and implemented on CLIM; this visual anomaly detection prototype system was developed via SC.

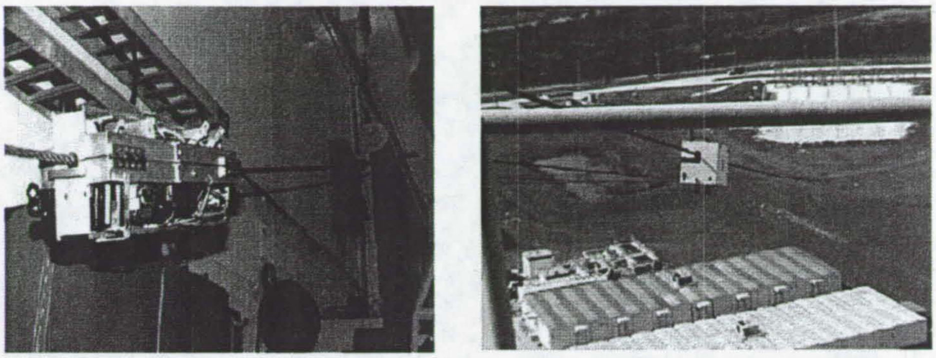


Figure 6. CLIM being tested at the laboratory (right) and the launch pad (left).

Using FRIEB, FRAT, and FRED the image goes through segmentation, object extraction, enhancement, filtering, and edginess detection; FRAT binarizes image preprocessed via FRIEB and FRED; a selective blob detector picks image regions with high edginess activity; morphological, geometrical, and fuzzy edginess values are computed for each region and used them as inputs to a Probability Neural Network (PNN) learning system.

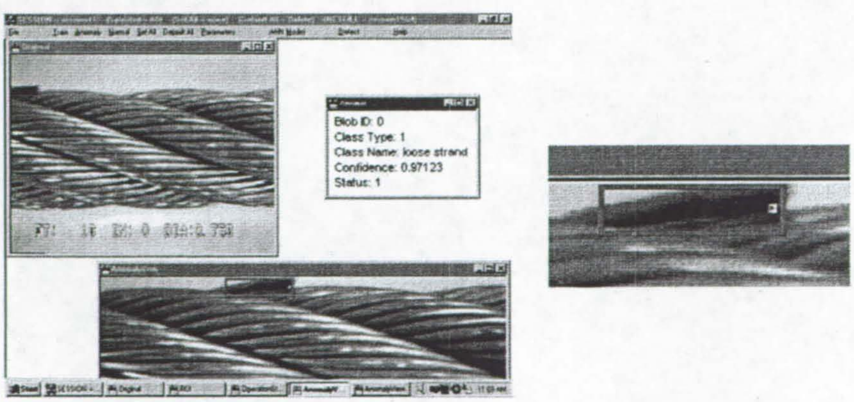


Figure 7. Loose strand detected by the system and indicated in separate windows.

Preliminary tests were conducted to detect loose strands. Figure 7 displays the software front end developed at KSC to show the results of the firing part of the ANN-GA scheme. As illustrated in figure 4, the system also shows detected anomalies in a separate window.

The window on the left corner of figure 4 displays the original image as acquired by the system in real time; the window on the bottom is generated by the system to display the image holding the anomaly indicated with a red rectangle. An additional window (white background) in figure 4 is also generated by the system to display the type of anomaly class found and its estimated confidence factor rated from 0 to 1 (being 1 the highest confidence).

3.3. Object Recognition within an Image via Edge Detection and Morphological Properties Estimation.

In contrast with conventional moving-object detection approaches, a general FR-based algorithm was developed to detect moving objects without the need of consecutive image frames. This general object detection algorithm was implemented to detect distant birds moving toward the Space Shuttle launch pad. The detection is performed on a single image frame by detecting edges via FRED to form blobs that are classified as birds based on key morphological properties (edginess and contrast) of the blobs. Only those blobs (formed by edge detection via FRED) with edginess and contrast values typical for birds are classified as birds. Figure 8 shows two image examples of bird detection via the proposed algorithm. In the first image example (top image) of figure 8, four distant birds are detected using a single image frame; the distant birds are considerably faded in the image as shown in cropped and magnified images of two of the four detected birds. In the second image example (bottom image) of figure 8, two birds are detected; the two detected birds are much closer and their detection happens to be more obvious.

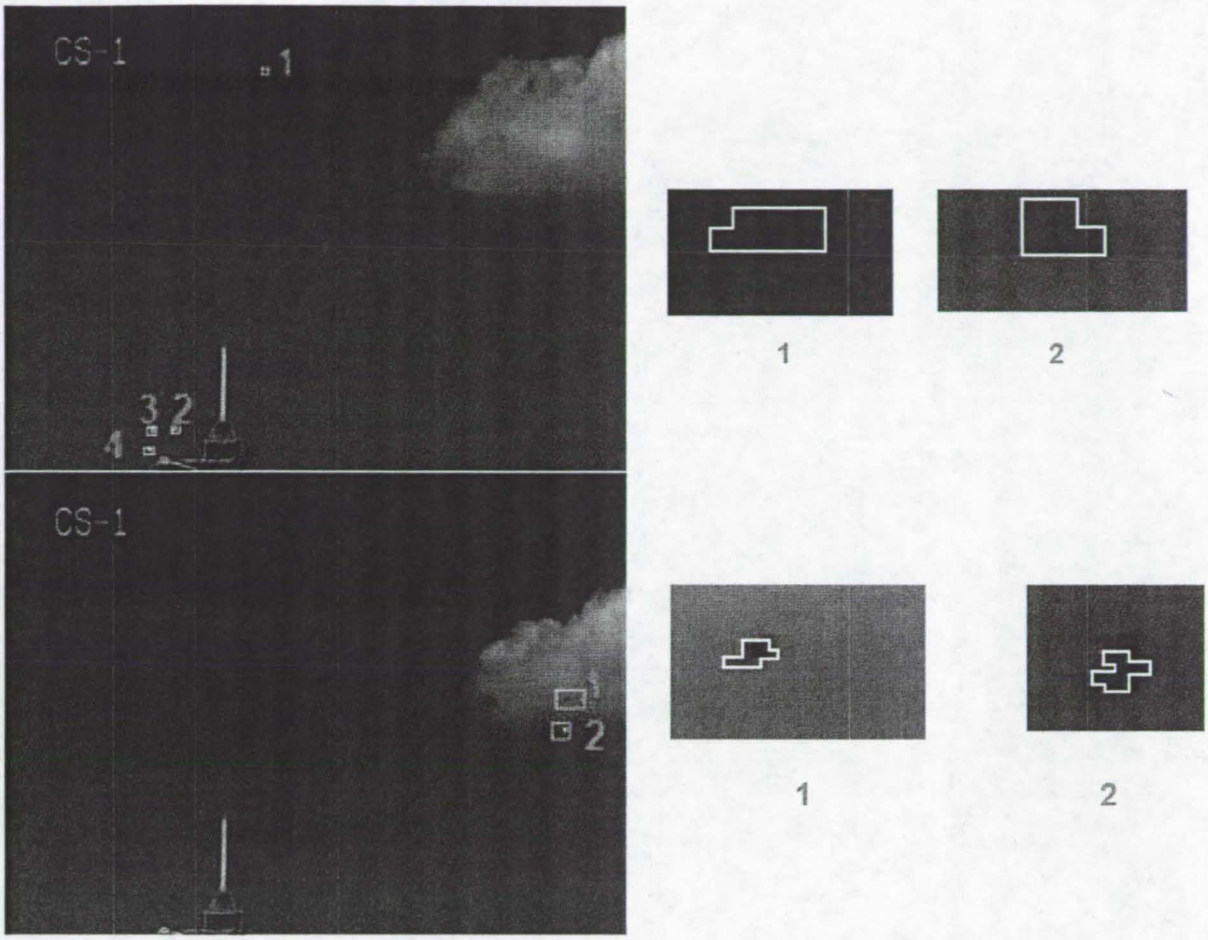


Figure 8. Examples of bird detection via the proposed SC-based scheme.

In the top image of figure 8 four distant and hard-to-see birds are detected; two of them are cropped and magnified to the right. In the bottom image of the same figure, two closer birds and easier-to-see are detected; both are cropped and magnified to the right.

Existing moving-object detection approaches are based on the difference between two consecutive image frames leading to the detection of objects located in different positions within two or more consecutive image frames. In this particular application (distant bird detection), the image difference approach does not work as expected since distant birds sometimes remain "suspended" and practically do not move during a considerable number of image frames. The motion of clouds, especially small clouds leads to false detection of birds if the difference between consecutives image frames is used. Image distortion caused by changing atmospheric conditions is a time-variant phenomenon leading to false detection of birds, as image pixel values of the image background do not remain constant. FRED-based edge detection scheme is used to form blobs; the blobs are classified based on key morphological properties that lead to the distinction and extraction of the blobs containing birds.

Blob classification based only on edginess morphological value leads sometimes to false detection of birds; some blobs containing clouds yield similar edginess values expected for birds. Contrast, another morphological property of gray-scaled images, resolves this false detection problem. Figure 9 illustrates how the addition of contrast value solves the false classification predicament that occurs sometimes when only edginess morphological value is used to classify gray-scaled image blobs formed via edge detection using FRED.

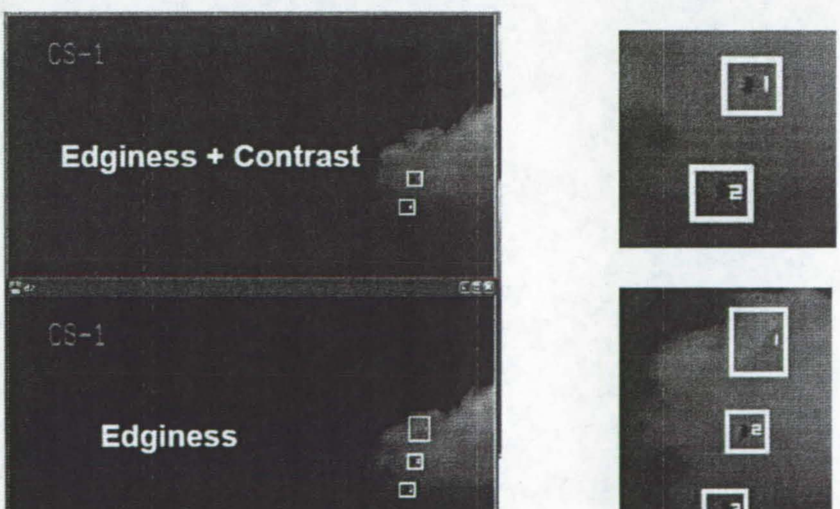


Figure 9. Blob selection based only on edginess value leads sometimes to false detection of birds; some edge-based blobs containing clouds yield similar edginess values expected for bids. The contrast value resolves this false classification problem.

Human vision is able to detect and distinguish particular objects (in our case birds) by seeing a single image regardless if the object is moving or not. The proposed algorithm also detects and distinguishes an object by analyzing a single image; in contrast with conventional algorithms, it does not need consecutive image frames to detect moving objects. Edge detection is naturally performed by human vision to locate object boundaries, the different morphological properties of the areas under those detected edges lead to the recognition of the different objects within the scene or image. The proposed algorithm mimics the human vision (in a very primitive and basic way) in the use of morphological properties to distinguish objects on images.

3.4 Space Shuttle Columbia Accident Investigation

A set of FRAT-based imaging techniques was utilized to support the Space Shuttle Columbia accident investigation on the detection and trajectory-velocity estimation of the foam debris that hit the Orbiter's wing. Two image acquisition sources, running at different frame rates and acquiring Shuttle's images from different angle views and positions, were used to automatically detect the foam debris, determine its borders/edges, and estimate its 3D trajectory as well as its respective 3D speed. The detection of the foam debris and determination of its respective borders at each one of the 2D image frames acquired by two different image acquisition sources were performed by FRAT-based techniques. The image techniques used here were able to autonomously (not interactively) detect the blobs containing the foam debris from two different image acquisition sources, one a film camera with a relative good resolution and definition and the other a video camera with a poorer resolution and definition.

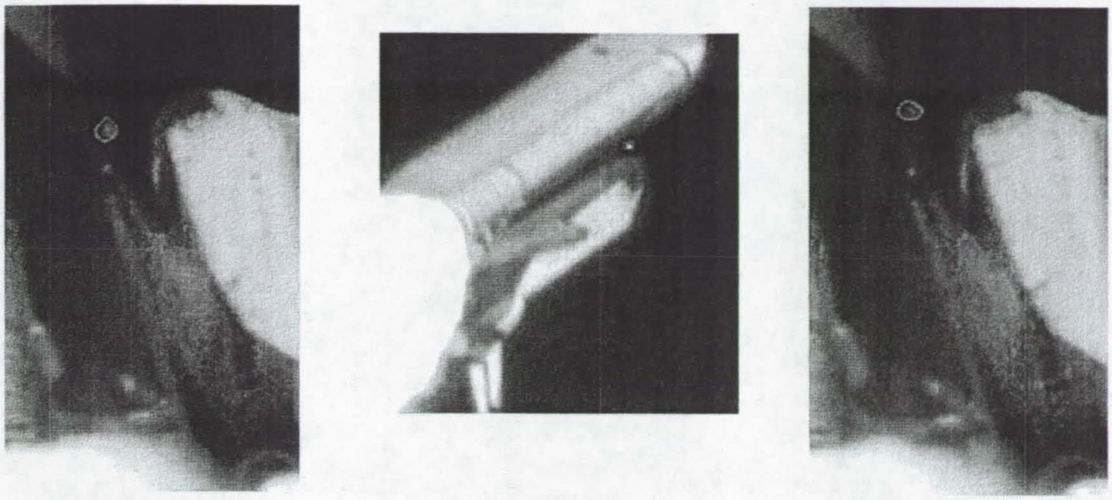


Figure 10. Three Columbia images acquired at a consecutive sequence using two different image acquisition sources; a film camera acquired the first and third images and a video camera acquired the second image. FRAT allowed the detection and border determination of the foam in each image. Using the relative 2D location of the foam at each image and finding the interception of their 3D extension the 3D location of the foam can be estimated.

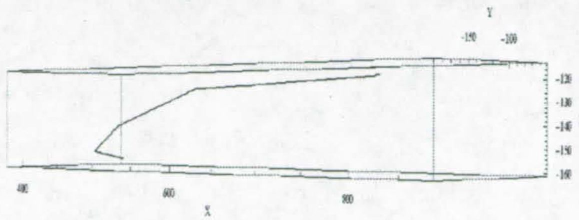


Figure 11. Estimated 3D trajectory of the foam before hitting the Shuttle's wing.

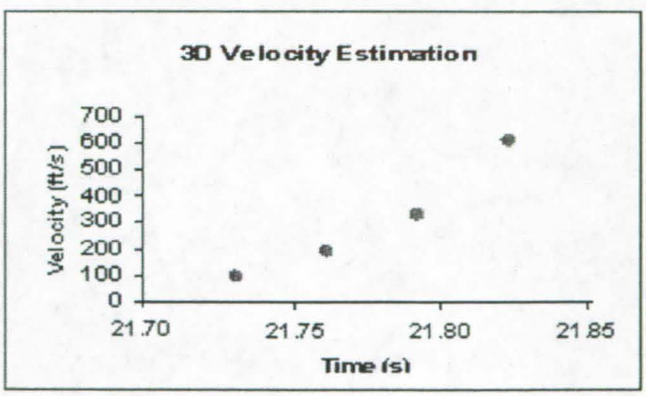


Figure 12. Estimated 3D foam velocity using the 3D position of figure 8 and the time recorded by the image acquisition sources.

Figure 11 shows the estimated 3D trajectory of the foam using four sets of three consecutive images from two different image acquisition sources (film and video) as shown in figure 7. Figure 9 shows the total 3D velocity computed using the trajectory shown in figure 8 and its respective time. These techniques also compute image blob geometrical properties such as area and center of mass. The center of mass of each debris blob was automatically calculated and used as the starting point of the respective 3D location line. A scaled 3D Shuttle model was used to manually determine the angle view of each 2D image acquired by the two image acquisition sources (film and video).

3.5 Other applications

The above FRED-based technologies have also proved their potential in enhancing x-ray images used to screen hard-covered items leading to a better visualization. Since the appearance of an x-ray film image is a plane in two dimensions of a structure built in three, the image is seen to contain a number of regions within the object superimposed on the background level. Therefore, to extract the contours of these different regions, it is necessary to have prior enhancement of the contrast levels among them. The FRED-based enhancement technique developed at NASA successfully deals with these problems.

Preliminary tests to enhance x-ray images acquired at Johnson Space Center to screen pyrotechnic devices were conducted with very promising results as shown in figure 10.

This FRED-based screening enhancement might be applied to x-ray images currently acquired to screen luggage at airports, containers in terminal ports, etc. Figure 11 shows another example of image enhancement of a saturated gray-scaled image saturated via FRED. Details hidden at saturated regions of both images in figures 10 and 11 are revealed as FRED extracts their edges, even the faintest ones using variable scanning windows sides.

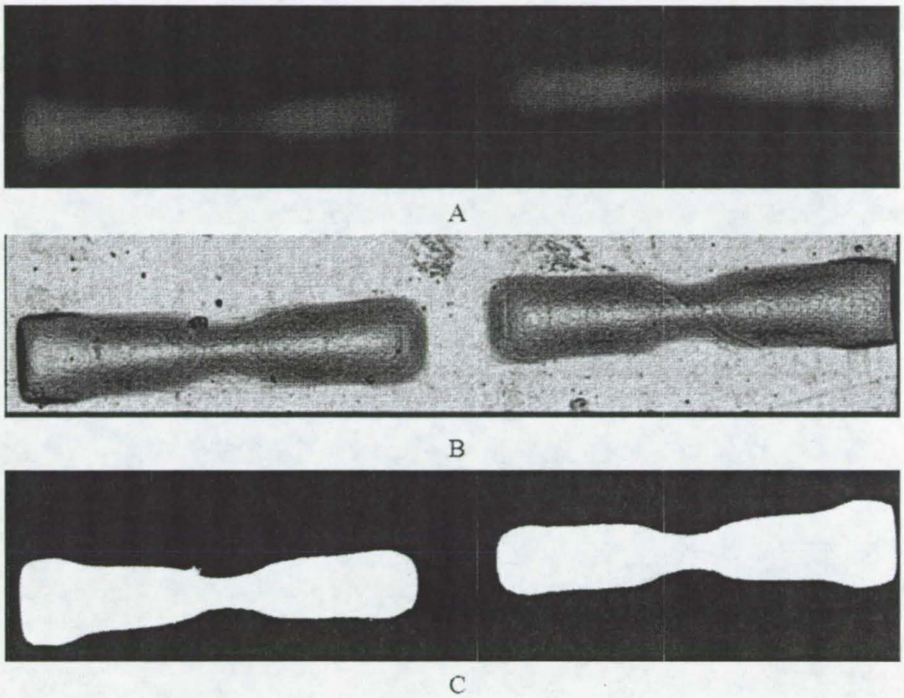


Figure 13. Enhancement and segmentation of x-ray images via FRED and FRAT respectively. A) original x-ray image of a pyrotechnic valve, B) Enhancement via FRED, C) Segmentation via FRAT.

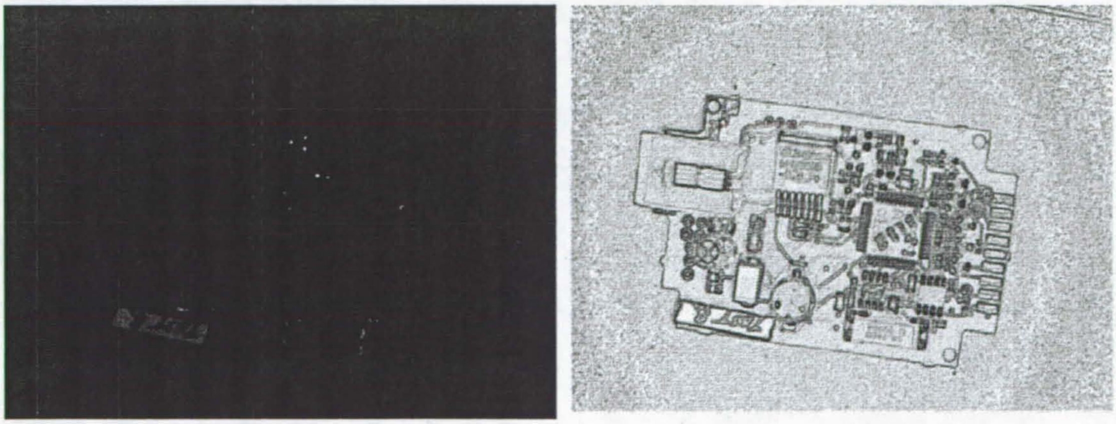


Figure 11. Enhancement of saturated gray-scaled image via FRED

References.

[1] Chi, Z., H. Yan, and T. Pham. (1999). Fuzzy algorithm with applications to image processing and pattern recognition, advances in fuzzy systems applications and theory, Vol. 10, World Scientific Publishing Co., Pte. Ltd., Singapore.

Di Zenzo S., Cinque L., and Levialdi S. (1998). Image thresholding using fuzzy entropies, IEEE Trans. Syst., Man, Cybern.

Dominguez, J. and Klinko S. (2004). Image Analysis via Fuzzy-Reasoning Approach: Prototype Applications at NASA. IEEE International Conference on Fuzzy Systems and Neural Network. Budapest, Hungary.

Dominguez, J. (2004). Edge Extraction and Image Binarization via Fuzzy Reasoning. Center for Imaging Science (CIS) at Rochester Institute of Technology (RIT). www.cis.rit.edu/info/IA_S2004_files/DominguezCharts.pdf

Dominguez, J. and Klinko S. (2003). Fuzzy Reasoning Aids Image Data Processing. NASA Technology Brief.

Dominguez, J. and Klinko S. (2003). Visual Anomaly Detection System Prototype. NASA KSC Research and Technology 2003 Annual Report.

Montana D. (2000). Neural Network Wight Selection Using Genetic Algorithms. vishnu.bbn.com/papers/hybrid.pdf.

Herman I., Melançon G., Scott M. (2000). Graph visualization and navigation in information visualization: a survey, IEEE Transactions on Visualization and Computer Graphics.

Kohler J. (2005). Imaging Technologies Strive to Protect America: Aiding Homeland Security. NASA Technology Innovation.

Saha P., Udupa J., and Odhner D. (2001). Scale-based fuzzy connected image segmentation: Theory, algorithms and validation, Computer Vision and Image Understanding.

Schaffer J., Whitley D., and Eshelman L. (1992). Combinations of genetic algorithms and neural networks: a survey of the state of the art, Proceedings of the IEEE Workshop on Combinations of Genetic Algorithms and Neural Networks.

Specht D. (1990) Probabilistic neural networks, Neural Networks.