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NEURAL NETWORKS:
ALTERNATIVES TO CONVENTIONAL TECHNIQUES
FOR AUTOMATIC DOCKING

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ABSTRACT

AUTOMATIC docking of orbiting spacecraft is a crucial operation that involves identification of vehicle orientation as well as complex approach dynamics. Success depends on the chaser spacecraft's ability to recognize the target spacecraft within a scene and achieve accurate closing maneuvers. In a video-based vision system, a target scene must be captured and transformed into a pattern of pixels. Successful recognition lies within the procedure that interprets this pattern. Due to their powerful pattern recognition capabilities, artificial neural networks offer a potential role in the interpretation process, and hence, in automatic docking. Neural networks possess many attractive features. They have an inherent ability to reduce the amount of computation time required by existing image processing and control software. In addition, it has been shown that neural nets are capable of recognizing and adapting to changes in their dynamic environment, enabling enhanced performance, redundancy and fault tolerance. Most neural networks are also robust to failure, that is, they are capable of continued operation with a slight degradation in performance after minor failures. This paper will discuss the particular automatic docking tasks which neural networks are capable of performing. The goal is to establish neural networks as viable alternatives to conventional techniques.

INTRODUCTION

AUTOMATIC docking of spacecraft is a challenging problem that demands the maturation of developing technologies. Upon recognition of a target during rendezvous, the chaser vehicle must perform a sequence of proximity maneuvers to accomplish the mechanical latching with the target spacecraft (Figure 1). The processing systems onboard the chaser must reliably identify, extract, and process target information within a possibly obstructed image scene. This processing must be repeatedly provided during vehicle closing maneuvers (Figure 2). Target attitude and position data must be determined by the vision

system so that the control system may initiate appropriate maneuvering commands for the propulsion system.

Automatic recognition of a target can be cumbersome, especially when the images contain scenes with structured background clutter, foreground visual obstruction, and varying intensity levels within the digitized images themselves [1]. The task is additionally complicated for automatic docking [2], due to the dynamic environment which the spacecraft may encounter (e.g., sun shadows, tumbling target, obstructed view of docking mechanism, and possible confusion caused by background objects).

In overcoming these difficulties, the realization of a fully automated system offers many attractive potential payoffs. These rewards include lowered mission costs, reduced risk factors for unmanned missions, increased attitude capability for satellite servicing, space debris capture, reboosting of spacecraft in decaying orbits, and orbital resupply [3].

In the next section, some conventional techniques being considered for incorporation in automatic docking systems will be examined. These include systems using radar, laser-based sensors, and video-based sensors. The concluding section will examine how neural networks may offer viable solutions to the problems encountered with the proposed conventional techniques.

CONVENTIONAL TECHNIQUES

A spacecraft's success in performing docking maneuvers is dependent on the accuracy of its sensors. Accurate range and range-rate information is required to maintain proper closure and avoid collision with the target spacecraft [4].

Radar can provide this information to some degree. The Soviet space program had performed automated rendezvous and docking since 1967, using radar-based systems. In such systems, the relative positions of two spacecraft are determined by the variation in signal strengths between antennas [5].
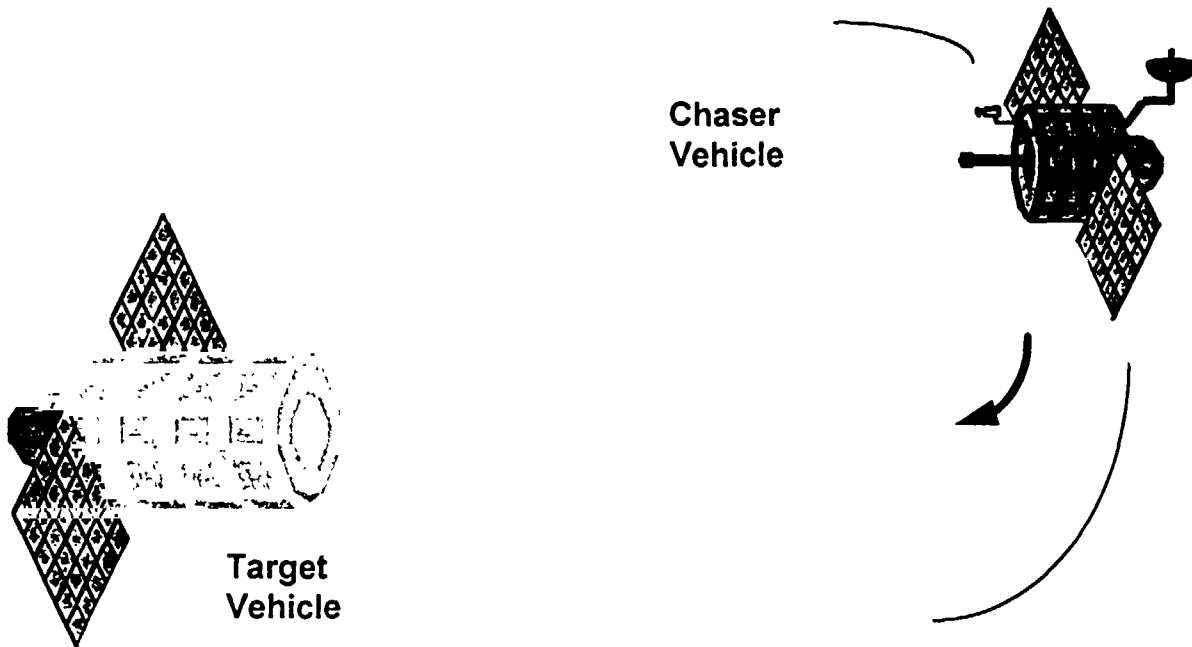
Figure 1. *Chaser and Target Vehicles during rendezvous.*

It has been incorrectly perceived that the Soviets used automatic control for all docking missions [6]. Despite regular success of automatic dockings of unmanned resupply ships with the Mir and Salyut space stations, automatic dockings of manned vehicles with the stations have been rare, if at all. The automated system has been routinely overridden in favor of manual docking. Reasons cited for failures were computer overloads, loss of radar signals, and antennae malfunctions [5]. Also, it should be noted that as the two spacecraft approach close proximity, radar range accuracy is influenced by multi-path problems and saturation of radar frequency signals. It follows that a more precise sensing technique is needed for reliable automatic docking.

An Automated Rendezvous and Capture (ARC) task team has been formed at NASA's Marshall Space Flight Center (MSFC) to develop a ground-based simulation for rendezvous and docking two unmanned spacecraft [7]. The docking maneuvers are planned to be controlled by a laser/video-based system that detects three retroreflective sensors embedded on a modified Remote Manipulator (RMS) target located on the target spacecraft by using lasers operated at two different wavelengths. Image scenes obtained using laser diode illumination will contain spots corresponding to desired reflection from the retroreflectors and other reflections [8]. Signal-to-noise enhancement is achieved by subtracting the non-illuminated scene from the target scene illuminated by the laser diodes. Onboard processing of the relative position of the three retroreflec-
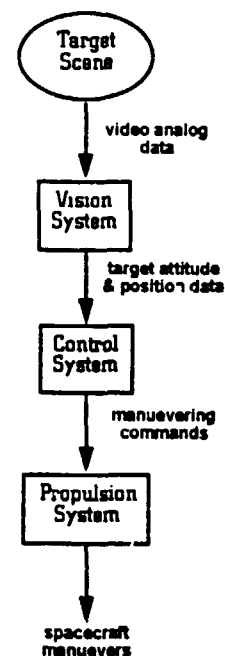

Figure 2. *Image Pipeline Process of Chaser Spacecraft.*

tors (within the video images) will provide range and translation displacement as well as relative attitude errors.

This technique has reasonable chance of success for a space-based mission given the restrictions in which it must operate. One restriction is that the method is designed to detect attitude stabilized targets (i.e., no tumbling, spinning, coning) and may fail if the target suddenly starts exhibiting dynamic behavior [7]. Another restriction is that the chaser spacecraft must always approach the target spacecraft so that the retroreflective sensors are consistently in the field of view (with no obstructive objects) and that the sensors are properly oriented in an upright position [4]. Also, although sun lighting of the target vehicle during docking maneuvers may be desirable, direct or reflected sunlight may interfere with the optical sensors [9]. Additionally, it should be pointed out that initial detection and identification of the three retroreflective sensors are non-trivial in a severe noise environment. In other words, the signal-to-noise enhancement may not be able to eliminate every false spot, causing misidentification of the three sensor dots [8]. It follows that the lack or loss of laser signal feedback from the target spacecraft would cause an abort from the attempted rendezvous [9]. Given these reasons, one may deduce that the ARC method lacks the ability to adapt to an unstable target and to environmental changes. A more adaptable method may be needed for a general case solution to the possible complexities of automatic docking.

Image-based (video) systems using such methods as Fast Fourier Transforms (FFTs) or syntactic pattern recognition, offer many advantages such as relative hardware simplicity and reprogrammability [10]. These advantages must be weighed against the disadvantages of these systems, such as limited operational range, response time limitations, poorer accuracy at greater distances, and sensitivity to lighting conditions. However, with properly designed algorithms and targets, these disadvantages can be minimized for many important vision applications [10].

The intent of this paper is not to enumerate all of the conventional techniques but to provide adequate information for comparison to neural network methods. Table 1 lists some of the many technologies embedded in conventional techniques. The next section will discuss how neural network techniques can be embedded in a vision system for video-based automatic docking. The objective is to develop a scheme which overcomes the previously stated limitations associated with conventional techniques. The scheme will focus on using self-adapting neural networks, since they offer promise for successful recognition in the dynamic environment in which the chaser spacecraft must operate.

| Radar |
| Laser-based sensors |
| Video-based sensors |
| Global Positioning System (GPS) |
| Fast Fourier Transforms (FFTs) |
| Portable/programmable optical hardware |
| Optical Correlators |

Table 1. *Some Technologies of Conventional Techniques*

NEURAL NETWORK TECHNIQUES

THE primary function of a vision system for automatic docking is to determine the three-dimensional relative position and attitude of a target vehicle from a two-dimensional image representation [11]. Successful recognition relies on the system's ability to correctly interpret the image scene. Problems that plague systems containing conventional vision techniques are caused by the enormous computational power required to process images [12]. It should be noted that many of the required computations for target recognition can be achieved simultaneously (i.e., in parallel). Furthermore, parallelism becomes essential in obtaining the real-time throughput required for automatic docking.

Due to their powerful pattern recognition capabilities and their massively parallel nature, neural networks are viable candidates for vision applications, and hence for automatic docking. Biologically inspired, a neural network is a system of highly interconnected processing units (called neurons) that can modify their dynamic behavior in response to their environment [13]. Neural networks have many advantages (Table 2). They are capable of making decisions at high-speed while maintaining fault tolerance, that is, they are capable of continued operation after moderate failures of individual components. Possessing this robust feature, they produce reliable results in the presence of noise or contradictory information. [14]. They also learn from experience and are capable of generalizing. Generalization allows a network to respond to (partial or incomplete) input that it has never seen before. Robustness and generalization provide a neural network the capability to self-adapt to changes in a dynamic environment. Given these attractive characteristics, one can conclude that neural networks make plausible candidates for performing automated vision tasks. For a more intense description of neural networks and specific architectures see [12], [13], [15], and [16].

massively parallel
adaptable to change
fault tolerant
distributed memory
good pattern recognizers
self-organizing
able to generalize

Table 2. *Some Characteristics of Neural Networks.*

It is the responsibility of the vision system to provide reliable position and attitude information to the control system (Figure 3). A proposed vision system for the chaser spacecraft, based on neural net techniques, consists of five major components: 1) image acquisition and digitization, 2) image compression, 3) edge detection, 4) image normalization, and 5) target attitude determination. Note that each component performs a specific task, given its se-

quential position within the image processing pipeline (Figure 3). The following example illustrates the operations performed by these components. The image acquisition and digitization component, consisting of a video camera and frame grabber, is subjected to a target scene. An analog signal of the target is captured and digitized into a 256 x 256 pixel image. Image compression reduces the image to a 32 x 32 pixel image. A contour of the target is then extracted using edge detection. The contoured image is centered and then scaled by an image normalization procedure. In the process of doing so, the translational displacement is calculated and supplied to the control system. The docking target attitude determination component calculates the rotational displacement of target from the normalized contoured image. The rotational displacement is then output to the control system.

The individual components of the vision system will now be examined for possible replacement by neural networks (Table 3). The function of the image compression component is to reduce the 256 x 256 image provided by the frame grabber down to a 32 x 32 pixel image. Reduc-
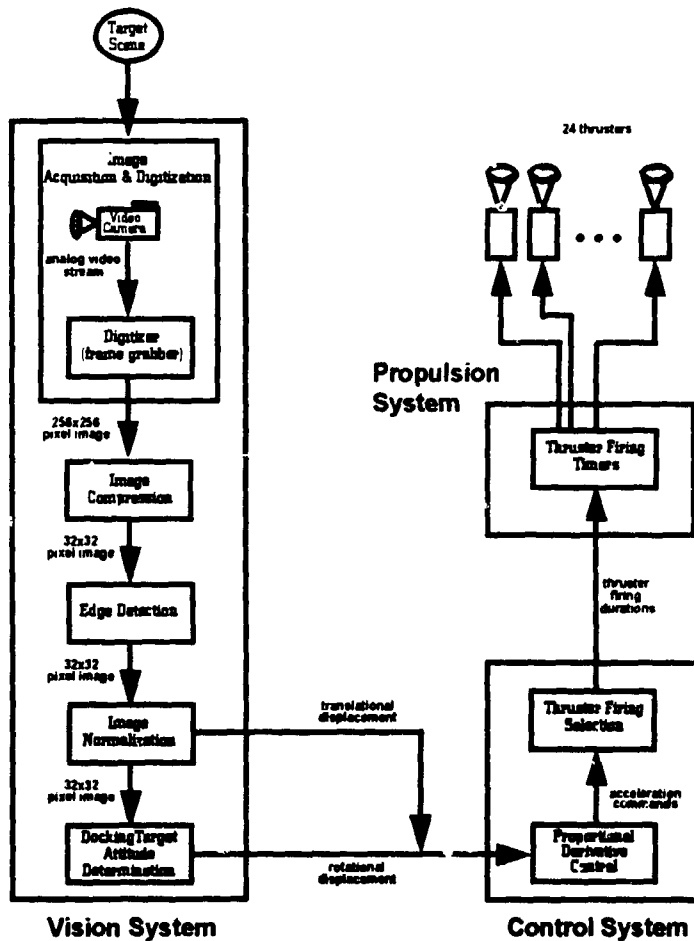
Figure. *Automatic Docking Tasks.*

ing the image size may be necessary to obtain the required real-time throughput. Conventional algorithms, such as pixel averaging techniques, exist that can perform the required compression [14]. However, if the compression cannot be performed within the maximum time allowed (to achieve real-time throughput), another approach is warranted. By taking advantage of the parallel power of neural nets, computational speeds can be maximized. Additionally, compressing the 256×256 image may be totally unnecessary, if the vision system meets the required throughput. Assuming image compression is essential, the counterpropagation network is a possible candidate for the task. Counterpropagation combines the Kohonen self-organizing feature map network with the Grossberg outstar, creating a three-layer paradigm possessing functionality not available in either alone [15]. This type of network is usually trained to perform pattern mapping [16]. For example, a pattern (image) of pixels can be mapped into another pattern of pixels of reduced size. Suppose that each image is divided into subimage regions [13]. Each subimage is then divided into pixels, which can be grouped into a vector. For a 256×256 pixel image, let each subimage be an 8×8 pixel region. This results in 32×32 regions total. Each region represents a vector input into the counterpropagation net. The net is then trained to output a predetermined average or thresholded pixel value representing the transformed region. Note each 8×8 pixel region of the 256×256 pixel image is mapped to 1 pixel within the 32×32 pixel image, resulting in a compression ratio of $8:1$.

Component	Neural Network
image compression	counterpropagation
edge detection	lateral inhibition
image normalization	Kohonen
target attitude determination	counterpropagation

Table 3. *Vision system components and their possible neural net implementations.*

The next step in the vision system processing pipeline is to perform edge detection on the compressed image. The approach is to identify contour boundaries within the image having distinct intensity values. A neural net well suited for this task is the lateral inhibition network [16]. The network is based on the lateral inhibition that occurs naturally in the auditory and visual biological systems. The edge-enhance properties of this network allow it to process noisy data in order to emphasize edge contrast. Within borderline edge areas of the input image, adjacent pixels having different intensity values will be enhanced in the output image. That is, light pixels will become lighter and dark pixels will become darker. The

image can be further thresholded to produce a 32×32 binary image consisting of a well-defined contour of the target.

The image normalization component centers the target within the scene and then scales it to some predetermined focal point. During this procedure, the translational displacement of the target can be computed and provided to the control system. The Kohonen self-organizing feature map is a good candidate for performing both the centering and scaling. This network specializes in characterizing the distribution of its input — in this case, the contour of the target. The contour center is calculated and the contour is centered within the image. A stored reference contour, representing the target at a designated orientation and distance, is then matched against the centered contour. The amount the centered contour must expand or shrink determines the scale factor for scaling the output image.

Determining the target attitude is a complicated task. The function of the target attitude determination component is to take the normalized image and produce the rotational displacement for input into the control system. If ample training data is available, a counterpropagation network can be configured to reliably perform this task. Presented a training set of contoured images obtained from a systematic set of designated reference images, the network can learn to associate each training image with the correct attitude of the target vehicle [17]. During operation, the trained network can determine the target attitude by interpolating between its best-matching stored images. Another advantage of using counterpropagation to perform the task is its ability to generalize on partially incomplete or partially incorrect input [13]. This enables successful recognition of a target within a degraded scene — such as the event that occurs when the target is suddenly casted with sun shadows.

Simulation of this proposed ... system can further measure the plausibility ... eural net techniques before a space-based m... ... empted. Table 4 compares a neural net-based sy ... ith a ... using the conventional laser/video (ARC ...

CONCLUSIONS

THE objective of this paper has been to: 1) acknowledge the difficulties in implementing a vision system for automatic spacecraft docking, 2) examine conventional vision techniques for weaknesses that could affect mission success, 3) emphasize the strengths of neural networks that overcome these weaknesses, and 4) establish neural networks as plausible alternatives to conventional techniques being considered for actual deployment.

In conclusion, conventional vision techniques such as the laser/video based method should perform ade-

quately within the restrictions imposed on them. The conventional methods need design enhancements for adapting in a dynamic environment. However, neural networks are capable of adaptation Due to their powerful pattern recognition and fault tolerance skills, neural nets provide a potential alternative for the design of an automatic docking system.

Laser/Video Based (ARC)
- Target must be attitude stabilized
- Target orientation assumed upright
- Performance unaffected by sunshadows and/or background
- Loss of laser signal feedback requires mission abort

Neural Net Based
- Stabilization not required since any orientation can be recognized
- No specific orientation assumed
- Must learn to adapt to environment changes

Table 4. *A comparison of the ARC method with a neural net-based method.*

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