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APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO MACHINE VISION FLAME DETECTION

J. A. NEAL, C. E. LAND, R. R. AVENT, R. J. CHURCHILL

AMERICAN RESEARCH CORPORATION OF VIRGINIA
P. O. BOX 3406
RADFORD VA 24143-3406

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John A. Neal, Cartlon E. Land, Rick R. Avent, Russell J. Churchill

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The U. S. Air Force has identified a need for rapid, accurate and reliable detection and classification of fires. To address this need, a proof-of-concept neural network-based, intelligent machine vision interface for the detection of flame signatures in the visible spectrum has been developed. The objective of the work conducted under this Phase I program has been to determine the feasibility of using machine vision techniques and neural network computation to detect and classify visible spectrum signatures of fire in the presence of complex background imagery. Standard fire detectors which rely on heat or smoke sensing devices tend to be slow and to react only after the fire reaches a significant level. Current electromagnetic sensing techniques have the desired speed but lack accuracy. The Phase I program approach to these problems used machine vision techniques to generate digitally filtered HSI (Hue, Saturation, Intensity)-formatted video data. Once filtered, these data were

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then presented to an artificial neural network for analysis. In the Phase I program, positive results were achieved in the application of neural networks in an intelligent HSI video data classification and analysis system for the detection of fires. The principal result of the Phase I effort was the implementation of a proof-of-concept fire detection system. Additional results included the development of image processing modules capable of intensity and hue thresholding, low pass filtering, image subtraction, region detection and labeling and HSI data normalization. In the Phase I system, these image processing modules were used to filter and format image data for processing by a neural network. Work conducted during the Phase I program resulted in a highly accurate neural network architecture. The Phase I neural network was trained to recognize expanding fire regions within an image using 137 training data sets consisting of 96 fire region sets and 41 false alarm region sets. After training was completed, this network was presented 23 test data sets containing 17 fire regions and 6 false alarm regions. The network demonstrated 100 percent accuracy with the training data sets and was also 100 percent accurate with the test data sets. This system was able to demonstrate reliable and repeatable detection of fire regions scaled to 4 by 4 feet at a range of 150 feet. The potential applications for this system, once fully developed in Phase II of the program, include installation in facilities requiring fire detection systems. For the U. S. Air Force, this would include aircraft hangars, ammunition depots and any facility containing high value assets and flammable materials. Phase II of the program will accomplish the feasibility established in Phase I by implementing a fieldable fire detection system. Part of this effort will include converting the system module algorithms to hardware implementations, thus significantly increasing system processing speed and reducing fire detection times to meet ever more demanding U. S. Air Force specifications.

EXECUTIVE SUMMARY

A. OBJECTIVE

The purpose of the work conducted under this Phase I program has been to determine the feasibility of using machine vision techniques and neural network computation to detect and classify visible spectrum signatures of fire in the presence of complex background imagery.

B. BACKGROUND

The U. S. Air Force has identified a need for rapid, accurate and reliable detection and classification of fires. Standard fire detectors which rely on heat or smoke sensing devices tend to be slow and tend to react only after the fire reaches a significant size. Optical Fire Detectors (OFDs) use limited-bandwidth infrared and ultraviolet electromagnetic sensing techniques to achieve the desired speed but lack the necessary accuracy. OFDs have repeatedly caused the inappropriate release of fire suppression agents which temporarily render a facility unprotected and require the use of expensive replacement agents. An optically-based fire detection system which captures and intelligently processes a broader range of the electromagnetic spectrum (such as the visible region) would eliminate false alarms while retaining processing speeds comparable to those of OFD's.

C. SCOPE

The principal result of Phase I was the development of a proof-of-concept system which uses image processing and neural network analysis techniques for accurate detection of fire from complex video imagery. The system developed consists of three subsystems: image capture, image processing and neural network analysis. The image capture subsystem extracts the hue, saturation and intensity (HSI) elements of a scene to form a color video image. The image processing subsystem eliminates all regions in an image that do not possess the intensity, hue and growth characteristics of fire. The neural network analysis subsystem compares the hue and saturation patterns of remaining regions to the hue and saturation patterns of fire for a final fire/no fire determination. The proof-of-concept fire detection system developed is slower than conventional OFD's since the image processing routines were implemented in computer software to facilitate algorithm development, testing and re-development for enhancement of detection accuracy.

D. METHODOLOGY

Color video image capture systems have been developed which extract either HSI or red, green and blue (RGB) elements of a scene to form a color image. HSI format was used in the proof-of-concept system developed since HSI characteristics can be correlated to fire imagery attributes using less complex processing algorithms than those required for RGB format. Neural networks were used to analyze hue and saturation patterns of video image regions since the derivation of a mathematical model to describe these patterns proved difficult and inaccurate.

E. TEST DESCRIPTION

The neural network employed in the proof-of-concept system developed was trained to recognize the hue and saturation patterns of regions in a video image that correspond to fire using 137 training data sets consisting of 96 fire region sets and 41 false alarm region sets. After training was completed, the network was presented 23 test data sets containing 17 fire region sets and 6 false alarm region sets.

F. RESULTS

The neural network used in the proof-of-concept system developed demonstrated 100 percent accuracy with the 23 data sets. In addition, the system demonstrated accurate detection of fire regions scaled to a four- by four-foot area at a range of 150 feet.

G. CONCLUSIONS

Experimental results suggest the following conclusions. The use of HSI video format as opposed to RGB video format reduces processing complexity and simplifies the interpretation of fire region characteristics. Intensity, hue and growth characteristics of fire can be used to differentiate regions in a video image that correspond to fire from regions that correspond to most false alarms sources. Regions corresponding to fire can be distinguished from regions corresponding to other false alarm sources through analysis of regional hue and saturation patterns by a counter-propagation uni-flow neural network. Detection speed using the algorithms employed in the Phase I proof-of-concept system would be less than five seconds if the image processing algorithms are implemented in computer hardware. The likelihood of a successful software-to-hardware conversion is high since high-speed image processing hardware is readily available as off-the-shelf components. The cost of parts for a hardware-based Phase II prototype system would be less than $10,000. The Phase III production model system would be of immediate use to the U.S. Air Force for implementation in aircraft hangars, ammunition depots and other high-risk installations.

H. RECOMMENDATIONS

The primary recommendation is conversion of the software-based Phase I proof-of-concept system to a hardware-based Phase II prototype system to achieve desired speed requirements. Development of a Phase II prototype system would benefit not only the U.S. Armed Forces but also private industry as reliable fire detection systems are needed to protect key facilities such as hospitals, where a fire could cause critical disruption of medical services, and nuclear power plants, where a fire could result in catastrophic environmental damage.

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PREFACE

This report was prepared by the American Research Corporation of Virginia, 1509 Fourth Street, P.O. Box 3406, Radford, Virginia 24143-3406, under contact F08635-90-C-0395, for the Air Force Engineering and Services Center, Engineering and Services Laboratory, Tyndall Air Force Base, Florida.

This report summarizes work done between May 1990 and November 1990. Mr. Douglas Schwartz was the AFESC/RDCF Project Officer.

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This technical report has been reviewed and approved for publication.

Douglas B. Schwartz
Project Officer

Neil H. Fravel, Lt Col, USAF
Chief, Engineering Research Division

Richard N. Vickers
Chief, Air Base Fire Protection
and Crash Rescue Systems Branch

Frank P. Gallagher, Col, USAF
Director, Engineering and Services
Laboratory

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SECTION I

INTRODUCTION

A. OBJECTIVE

The U. S. Air Force has identified a need for rapid, accurate and reliable detection and classification of fires. To address this need, a proof-of-concept neural network-based, intelligent machine vision interface for the detection of fire signatures in the visible spectrum was developed. The objective of this Phase I program has been to determine the feasibility of using machine vision techniques and neural network computation to detect and classify visible spectrum signatures of fire in the presence of complex background imagery. The benefit of this SBIR program is the development of a system capable of real-time recognition of fires utilizing machine vision and neural network technology.

B. BACKGROUND

Standard fire detectors which rely on heat or smoke sensing devices tend to be slow and to react only after the fire reaches a significant level. Current electromagnetic sensing techniques have the desired speed but lack the necessary accuracy. Optical Fire Detectors (OFD's) have repeatedly caused the inappropriate release of fire suppression agents which can render a facility unprotected and require the use of expensive replacement agents. In addition, OFDs can monitor only a limited radiation bandwidth and thus can collect only limited information about the presence of fire. The most desirable solution to this problem takes advantage of recent advances in machine vision and neural network computing for application in fire detection systems. The Phase I program approach to these problems employed machine vision techniques to generate digitally filtered HSI (Hue, Saturation, Intensity) -formatted video data. Once filtered, these data were then presented to an artificial neural network for analysis. Neural networks have been used successfully in the classification and recognition of complex input data such as those found in pattern recognition applications (Nestor, 1989; Klimasauskas, 1988; Touretzky, 1989).

C. SCOPE

In the Phase I program, positive results were achieved in the application of neural networks in an intelligent HSI video data classification and analysis system for the detection of fires. The Phase I program demonstrated the feasibility of developing a neural network video classification system which allows on-line monitoring, detection and classification of visible-spectrum fire signatures as derived from machine vision data. The principal result of the Phase I effort was the implementation of a proof-of-concept fire detection system. Additional results included the development of image-processing modules capable of intensity and hue thresholding, low-pass filtering, image subtraction, region detection and labeling and HSI data normalization. In the Phase I system, these image processing modules were used to filter and format image data for processing by a neural network. A detailed description of the system modules can be found in later sections of this report.

Work conducted during the Phase I program resulted in a highly accurate neural network architecture. A proof-of-concept neural network was trained to recognize expanding fire regions within an image using 137 training data sets consisting of 96 fire region sets and 41 false alarm region sets. After training was completed, this network was presented 23 test data sets containing 17 fire regions and 6 false alarm regions. The network demonstrated 100 percent accuracy with both the training data sets and the test data sets. In addition, the system was able to demonstrate reliable and repeatable detection of fire regions scaled to 4 by 4 feet at a range of 150 feet. The potential applications for this system, once fully developed in Phase II of the program, is the installation in facilities requiring fire detection systems. For the U. S. Air Force, this would include aircraft hangars, ammunition depots and any facilities containing high-value assets and flammable materials. Phase II of the program will accomplish the feasibility demonstrated in Phase I by implementing a fieldable fire detection system. This effort will include converting the system module algorithms to hardware implementations, thereby significantly increasing system processing speed and reducing fire detection times to meet ever more demanding U. S. Air Force specifications.

The overall goal of the Phase I research program was to demonstrate the feasibility of applying neural network information processing techniques to machine vision recognition of fire with an accuracy superior to traditional optical monitoring techniques. The innovation developed in this program is the application of neural network technolcgy as an intelligent interface to standard HSI video data acquisition systems for the more accurate detection of fire regions in background light as compared with currently available optical recognition techniques. The goal of this research program has been to develop a sophisticated video data interface using neural networks to provide simulated intelligence in the identification of visible-spectrum fire signatures. Specific objectives were as follows:

1. Evaluation of the Machine Vision Data

During the completion of this technical objective, the hue, saturation and intensity (HSI) characteristics of video imagery data of fire regions and potential false alarm regions were examined. Comparison of these regions with the HSI attributes of the background imagery allowed the identification of HSI characteristics unique to flame-like regions within the imagery. Questions addressed included which HSI fire region characteristics were well-defined and therefore could be processed by digital filtering and which characteristics needed the high resolution analysis of the neural network.

2. Identification and Acquisition of the Optimal Neural Network Paradigm

The goal of this technical objective was to determine and obtain the optimal neural network paradigm and appropriate simulation software for fire detection applications. Questions addressed included pattern recognition, associative memories, image processing and signal classification. All of these issues were considered in the selection of an appropriate neural network architecture.

3. Implementation of the Neural Network and Provision of User Interface

The network paradigm selected in Technical Objective 2 was implemented during the completion of this technical objective. A counter-propagation paradigm was implemented in the Phase I system. Questions addressed included the number of simulated neurons per layer, the number of layers, and the number and characteristics of the inputs and outputs.

4. Training of the Selected Neural Network with the Video Flame Data

The neural network architecture implemented in Technical Objective 3 was trained in this technical objective using training data sets generated from fire and false alarm imagery. The accuracy of the network with various numbers of inputs was observed and the results of neural network architecture modifications were compared. Questions addressed during this technical objective included the size and number of training data sets and the number of training repetitions required before the network accuracy leveled off.

5. Evaluation of Pixel Geometries for Compactness and Reliability

The input geometries and network nodes which had no apparent or deleterious effects on the accuracy of the network implemented in Technical Objective 4 were removed and the remaining architecture was adjusted for optimal reliability. Questions addressed during this effort included the determination of which input and node configurations ensured maximum operating efficiency and speed. The identification of optical input characteristics was used to define the digital image preprocessing algorithms required to generate the desired input data set attributes.

6. Optimization of the Completed Neural Network System to Determine Efficiency and Validity of the System

The completion of this objective entailed the design and implementation of a proof-of-concept, neural network-based, fire detection system. The system was designed to meet U.S. Air Force time-to-detection and resolution requirements while maintaining significantly fewer false alarm occurrences. than conventional optical fire detectors without degradation in fire detection sensitivity and accuracy. Questions addressed during this technical objective included characterization of realistic operating environments for which the system is targeted, image-preprocessing algorithm speed and efficiency optimization, anticipated false alarm scenarios and U. S. Air Force requirements of detection time accuracy and reliability.

In the Phase II program, the development of an intelligent video data classification and recognition interface will be finalized to include a fieldable fire detection system for use by the United States Air Force. The implementation will include a hardware-based, neural network system that will accept video data directly from video capture hardware and yield an output of the probability of fire being present and the nature of the fire. This system will be made available commercially under a Phase III program backed by private or venture capital funding.

SECTION II

METHODOLOGY

The goal of Phase I of this program, to evaluate the feasibility of developing a neural network image analysis system for fire detection applications, involved a set of experimental evaluations to satisfy the technical objectives and to establish the basis for the design of an accurate, reliable Phase II system to be commercialized in Phase III of the program. The Phase I technical program involved the evaluation of HSI-formatted flame imagery, the design of a neural network software architecture and preprocessing digital filters needed to implement the fire detection function, the software implementation of a proof-of-concept fire detection system and the evaluation of the Phase I prototype software. These topics are described in the following sections in relation to the background and associated work and to the work performed to achieve each of the technical objectives.

A. BACKGROUND AND RELATED WORK

Standard color video image processing usually is based on techniques which combine the red, green and blue (RGB) elements of color video imagery. Unfortunately, RGB processing algorithms represent an inherently complex and computationally intensive method of processing digitized video data. More recently color video frame grabbers have been developed which are capable of real-time video capture and generation of digitized imagery data in either RGB or hue, saturation and intensity (HSI) format. In RGB format, each pixel of a color image is characterized by three values which correspond to the amount of red, green and blue needed to define the color of the pixel. To analyze an RGB image, each value must be processed separately and then recombined to characterize image attributes.

The significance of the HSI format is that the hue data can be correlated to the visible spectrum "color" of the pixel, while the saturation gives an indication of color "wash out" and the intensity indicates pixel brightness. Each of these characteristics can be independently correlated to fire imagery attributes without complex processing algorithms. This reduces the amount of processing required to detect fire regions in a digitized video image. To capitalize on this reduction in image processing complexity and the resulting increase in processing speed, the Phase I fire detection system digital filtering modules process HSI-formatted video imagery. Once the HSI data have been filtered, the imagery is processed by an artificial neural network.

Artificial neural networks are designed to simulate the physical architecture of the neurons in the human brain and have demonstrated significant performance advantages over more conventional methods in pattern recognition applications. Artificial neural networks differ from traditional pattern analysis methodology in that the network can be "trained" by example using correlated input/output data sets. The application of neural network simulation technology to signal processing is becoming standard practice; however, the widespread application of such technology to the field of complex data interpretation and classification in video image monitoring has not yet occurred. Work has been performed in the area of recognizing and classifying cardiac sinus rhythms (Nestor, 1989; O'Reilly, 1989) and in the area of motor noise analysis (O'Reilly, 1989). However, these efforts have centered on recognizing specific signal patterns from a single source and not on real-time monitoring, classification and analysis of complex video imagery.

Typical neural network architectures support multiple node layers - an input layer, an output layer, and one or more hidden layers. The structure of the hidden layers is key to accurate and reliable network function. Too many neurons in the hidden layer will cause the neural network simply to "memorize" the input data files (Touretzky, 1989; Obermeier, 1989) resulting in a network which can give the proper response to the training data sets, but which cannot extrapolate results for data sets that differ from the training data sets (AI Ware, 1989). On the other hand, too few simulated neurons in the hidden layers will result in a neural network which will not properly converge during training (Pao, 1989; Khaidar, 1989; Touretzky, 1989; Obermeier, 1989) and which will give proper results only for the most recent set of training data, "forgetting" training data from the beginning of the training set. Careful selection and implementation of a network paradigm can lead to a balance between these two undesirable situations.

The ability to train a neural network is derived from multiple interconnections between weighted nodes (neurons). These node weights are randomized when the network is initialized and are altered by the network as training progresses. This allows the network to accord greater significance to certain inputs and less to others (Klimasauskas, 1988 and 1989; Pao, 1989). In this manner a pattern or process is learned during the training phase after which the network can recall an associated output when presented with an input pattern similar to the training data sets. When presented with an input pattern that is not an exact match with a pattern involved in the training, the neural network is capable of discerning which training pattern the unknown pattern most resembles and how similar the patterns are. This allows the neural network to interpolate input/output correlations as new input patterns are encountered.

Neural networks are computationally intensive during training; however, once a network is trained, input data can be processed at extremely high throughput rates, making neural networks a practical solution to real-time image processing applications. Neural network simulation is a relatively new technology which, for certain cases, has been able to define relationships between data sets that have defied more conventional algorithms and, in other cases, has been able to identify relationships which had previously gone unnoticed. Herein lies the strength of neural network simulations - the ability to derive a result for a situation or pattern never before encountered (Klimasauskas, 1988 and 1989).

The application of neural network simulation technology to video processing is becoming standard practice, but application to the field of complex data interpretation and reduction in video monitoring has not yet been fully developed. Recent work on complex signal analysis has been conducted by Anderson (1990) who used neural networks to analyze a complex simulated radar signal environment. Research is also being conducted on the use of neural networks to integrate and analyze the visual and acoustic cues in human speech for machine-based speech recognition applications (Yuhas, 1990). Neural network-based acoustic sensing has been conducted at the Siemens blower motor manufacturing facility. Previous efforts to identify faulty motors relied on human monitoring; a solution both time consuming and labor intensive. Conventional pattern recognition techniques were also inadequate because of insensitivity to noise differences. However, an artificial neural network system was able to identify noise problems in motors about ninety percent of the time (O'Reilly, 1989).

In a related area, Odin Corporation using neural networks was able to identify ignition problems in internal combustion engines. Such problems were not detected using conventional quality control systems (EET, 1990). Work has also been conducted in the area of recognizing and classifying cardiac sinus rhythms (Nestor, 1989; O'Reilly, 1989). These efforts centered on recognizing specific cardiac arrhythmias from a single sensor as opposed to continuous monitoring and classification of multiple cardiac rhythm signals. Recent work on superconducting neural networks has resulted in the award of two patents to the Naval Research Laboratory in Bethesda, Maryland (Johnson, 1990).

B. EVALUATION OF DIGITIZED VIDEO IMAGERY

Technical Objective 1, the evaluation of machine vision data, was approached through an investigation of the hue, saturation and intensity (HSI) characteristics of digitized imagery of flame regions and false alarm regions. This section outlines the technical program that was conducted to determine which video data aspects are pertinent to the problem of visible-spectrum, machine vision fire detection. The technical effort is divided into three segments: a) aspects of a scene that should be captured in an image, b) aspects of an image that should be used to extract regions corresponding to flames in the preprocessing stage, and c) aspects of regions corresponding to flames that should be used as input data to the neural network. These segments are discussed in the following sub-sections.

1. Aspects of a Scene That Should Be Captured in an Image

Video acquisition equipment can provide video data in either RGB (Red, Green, Blue) or HSI (Hue, Saturation, Intensity) format. *Hue* is the spectral aspect of a color and ranges from red to yellow to green to cyan to blue to magenta and then back to red. The hue scale is a "circular" scale with red represented by both the lowest and highest limits of the scale. *Saturation* is the purity of a color in terms of how faded or deep the color appears to be. The saturation scale ranges from completely faded (white) to completely pure. *Intensity* is the brightness of a color and ranges from completely black to completely white.

The HSI representation is considered superior to the RGB representation in image processing applications since the hue, saturation and intensity components of a color are highly uncorrelated, i.e., highly independent of one another, whereas the red, green and blue components of a color are highly correlated. Because hue, saturation and intensity are highly uncorrelated, information conveyed in the HSI representation is, in many cases, easier to interpret than information conveyed in the RGB representation. Humans tend to interpret and to describe color in terms of hue rather than in terms of red, green and blue quantities. For example, the color yellow is specified by the term "yellow" instead of "equal quantities of red and green with no blue." Since image processing algorithms are automated implementations of how humans interpret images, more efficient algorithms can be developed as image data are better understood.

2. Aspects of an Image That Should Be Used to Extract Fire Regions

Experimentation has shown that regions in color video imagery corresponding to fire could be correctly extracted using hue- and intensity-level histograms derived from the image as a whole. The *hue* levels displayed by regions corresponding to fire tend to fall between red and yellow and between magenta and red as shown in **Figure 1**. The *intensity* levels displayed by regions corresponding to fire tend to be high as shown in **Figure 2**. The cutoff intensity of regions corresponding to fire is a function of the saturation setting (not to be confused with the HSI saturation component) of the scanning camera employed and is experimentally obtained. Imagery used in the experimentation was obtained from a high-resolution color CCD-based camera. The saturation levels of regions corresponding to fire tend to occur at all levels and thus can not be used in the region extraction process.

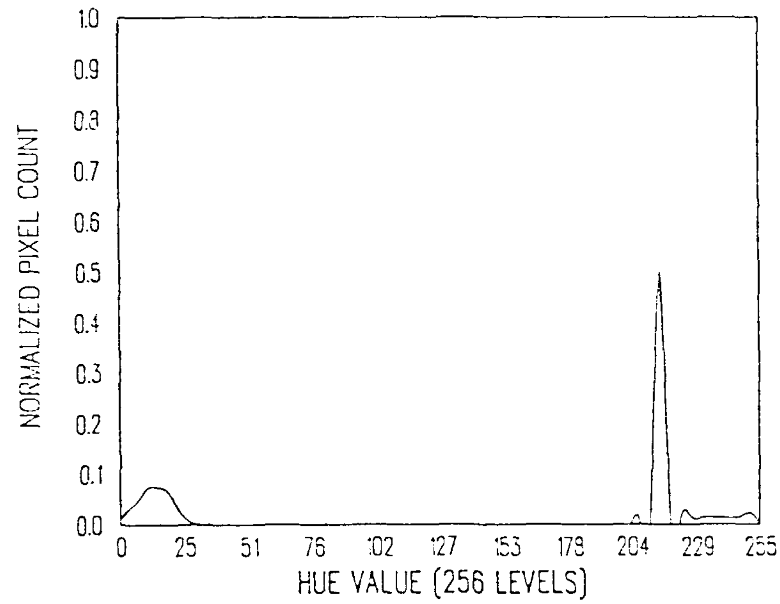


Figure 1. Typical Hue Histogram of a Region Corresponding to Fire

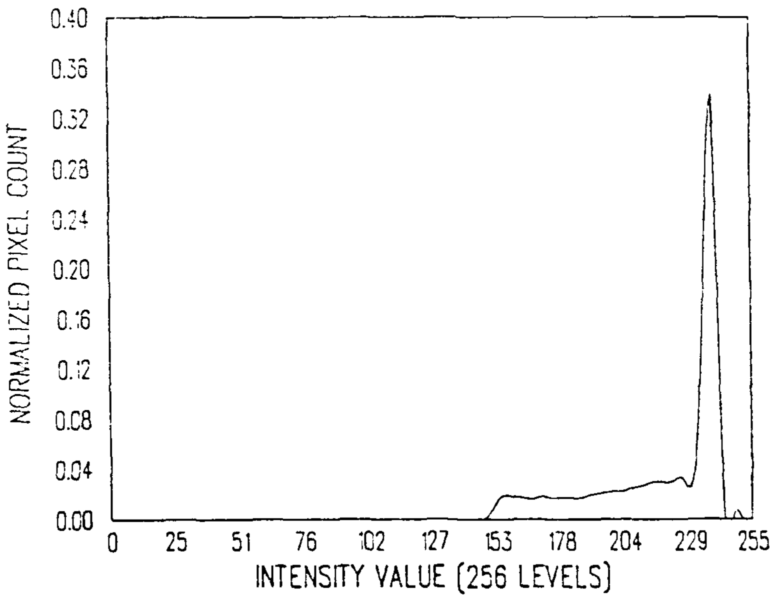
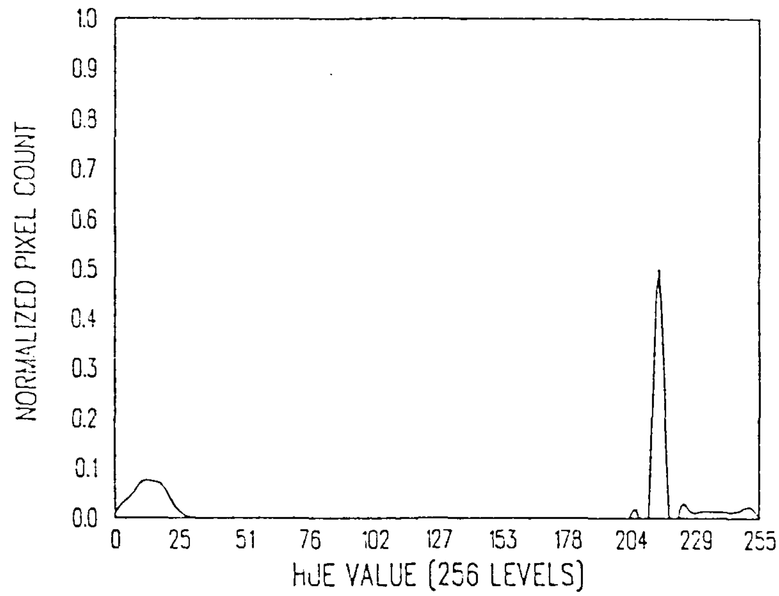


Figure 2. Typical Intensity Histogram of a Region Corresponding to Fire

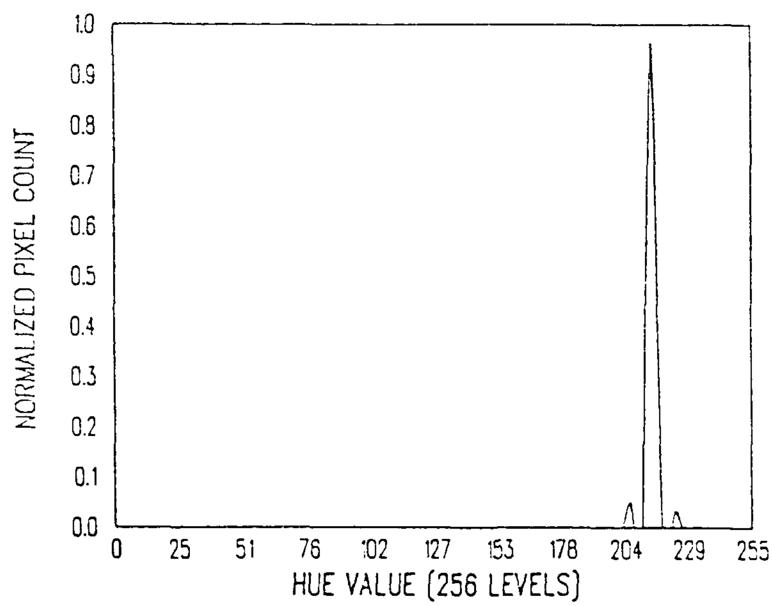
3. Aspects of Fire Regions That Should Be Used as Input Data to the Neural Network

Experimentation has shown that regions in a color video image corresponding to nonfire phenomena can possess hue and intensity levels similar to those possessed by regions corresponding to fire. Phenomena possessing hue and intensity levels similar to those possessed by fire include direct sunlight, reflection of sunlight from glass, reflection of sunlight from metal, reflection of sunlight from wood and indoor lights. Further experimentation revealed that the profiles of hue- and saturation-level histograms derived from regions corresponding to fire tend to differ in shape from the curves of hue- and saturation-level histograms derived from regions corresponding to other light-producing phenomena. A typical variation in hue for regions of fire and for false alarm-regions is shown in **Figure 3**, while **Figure 4** shows a typical variation in saturation. Curves of intensity-level histograms derived from regions corresponding to flames could not be distinguished from the curves of intensity-level histograms derived from regions corresponding to other light-producing phenomena.

Although the difference in shape between histograms derived from regions corresponding to two dissimilar light-producing phenomena may be substantial as shown in **Figure 3**, the shapes of histograms derived from regions corresponding to similar light-producing phenomena are not exact as shown in **Figure 5**. The derivation of a mathematical expression describing the histogram shape of a region corresponding to a particular light-producing phenomena proved difficult and, in some cases, impossible for conventional image processing algorithms. This type of complex data interpretation represents an application which is well suited for solution through neural network analysis techniques. Instead of developing a closed mathematical description of histogram profiles, neural network analysis achieves a solution through the construction of a two dimensional matrix of input nodes, hidden layers and output nodes. The nodes contained within the matrix are assigned analysis "weights" which give certain analysis points or nodes more influence on the output value than other nodes. The resulting architecture can thus develop a "best case" model for the input/output correlation and provide a probability assessment of the correct output for a given input set.

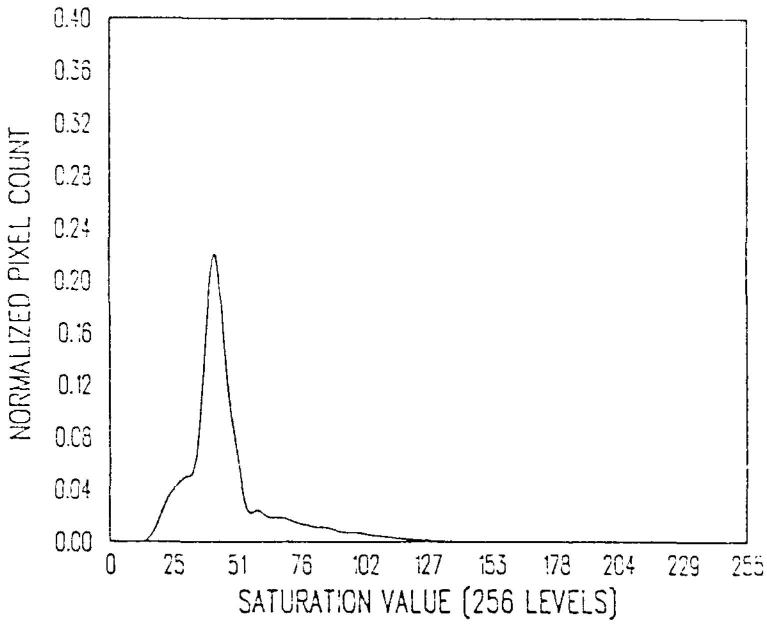


a) Region Corresponding to Fire

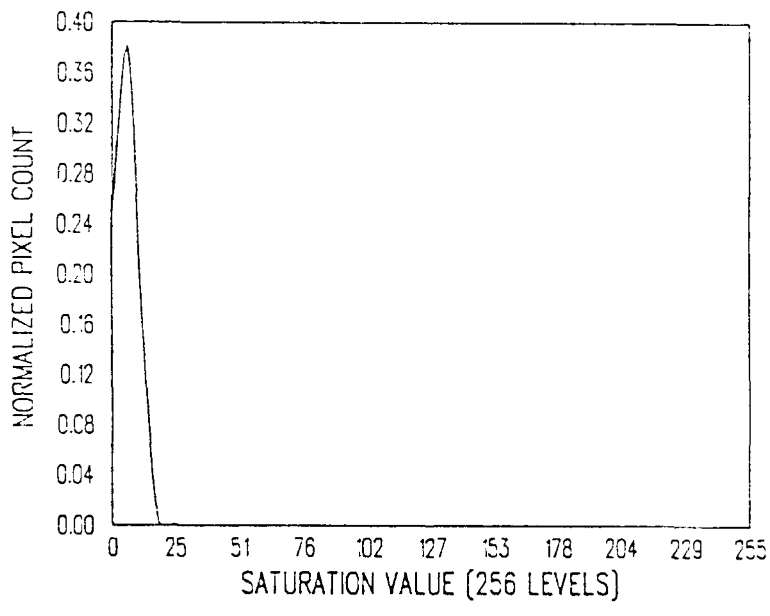


b) Region Corresponding to a Typical False Alarm

Figure 3. Typical Hue Histograms of a Fire Region and a False-Alarm Region

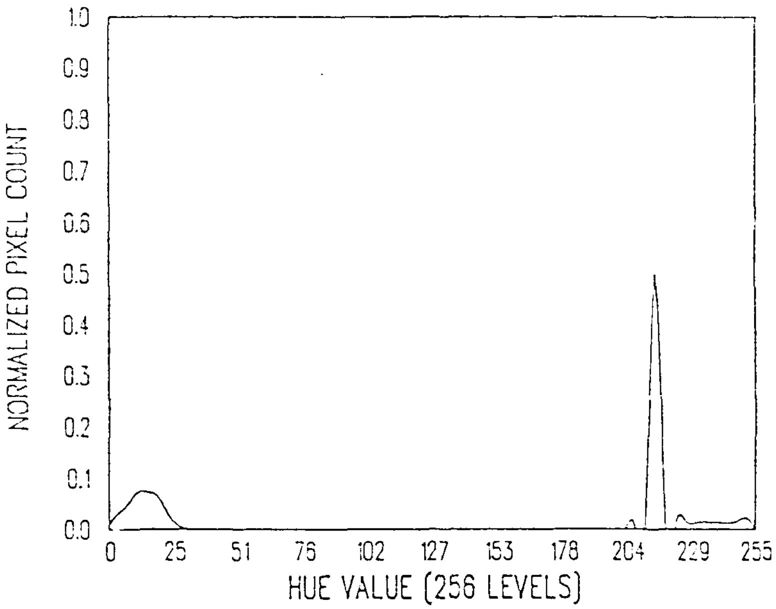


a) Region Corresponding to Fire

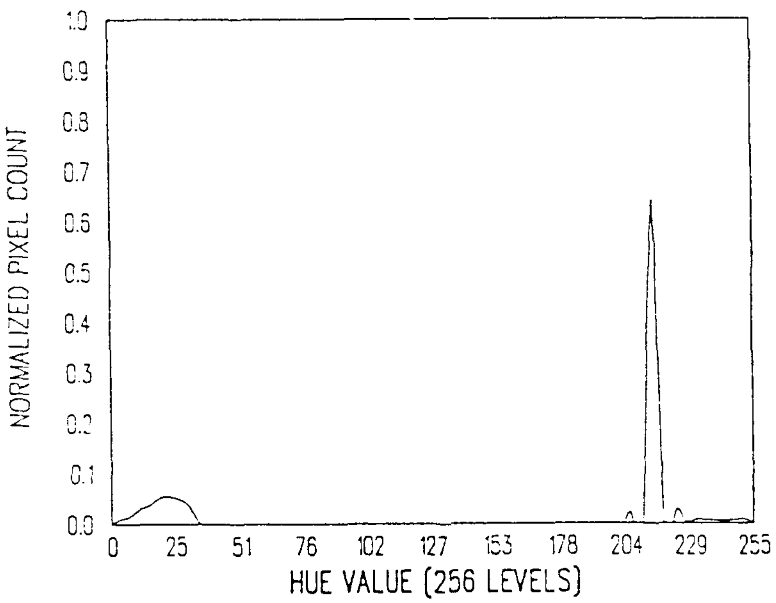


b) Region Corresponding to a Typical False Alarm

Figure 4. Typical Saturation Histograms of a Fire Region and a False-Alarm Region



a) Flame Region 1



b) Flame Region 2

Figure 5. Hue Histograms of Two Different Flame Regions

C. SELECTION OF NEURAL NETWORK PARADIGM

Technical Objective 2 involved the identification and acquisition of a neural network paradigm. Preliminary efforts were directed toward the examination of hue values from video imagery. The hue histogram of an entire image was compiled and used as input to a neural network. Hue histogram data were 256 bytes long with a single-digit fire indicator as an output. Initial efforts employed a network using functional-link expansion with back-propagation of errors.

The functional-link expansion has demonstrated promise in the identification of complex patterns without the need for excessively complex network architectures and paradigms (Pao, 1989). The functional link expansion paradigm is based on an expansion of the given inputs by generating functional combinations of the original input values and then using these functional values as additional system inputs. This process exponentially increases the number of effective network inputs for an original input data set. This recursive expansion of the inputs has been shown to eliminate the need for hidden network layers for some applications (AI Ware, 1989).

During the initial program efforts, some success was noted using functional link expansion with 256 hue histogram data inputs; however, the system was limited due to the inability of the N-Net 210 software to utilize extended memory space for the implementation of expanded network architectures. It was determined that the internal geometries of the pattern recognition algorithms that needed to be developed by the neural network paradigm were too complex for an unassisted linear network, such as functional link expansion, to model adequately. To counter this problem, hidden layers were incorporated in the network structure. Hidden layers have demonstrated the ability to map complex relationships between data inputs and desired outputs (Morse, 1989; Klimasaukas, 1989).

As the network development effort progressed, it was determined that a significant increase in the functional efficiency of the Phase I network could be achieved without significant degradation in analysis accuracy by removing the functional link expansion, thereby, leaving a counter-propagation of errors model. It was ascertained that the "function" of the functional link expansion model could be more efficiently duplicated by adding hidden layers based on the counter-propagation uni-flow network paradigm.

The structure of the counter-propagation uni-flow network is shown in Figure 6. This type of network maps a set of normalized input vectors, X, to a set of output vectors, Y. For the fire detection system developed, X consists of H_H and H_S, the normalized hue and saturation histograms, respectively, extracted from an image region obtained by the image processing subsystem that is described in SECTION II, Subsection G, of this report. The set of output vectors, Y, consists of the vectors $[10\ -10]^t$ and $[-10\ 10]^t$, which correspond to the conditions "fire" and "no fire", respectively. During training, the Kohonen layer measures the cosines of the angles between the input vectors, X, and a set of weight vectors, W. The processing element having the weight vector that produces the smallest cosine value is assigned the highest output value

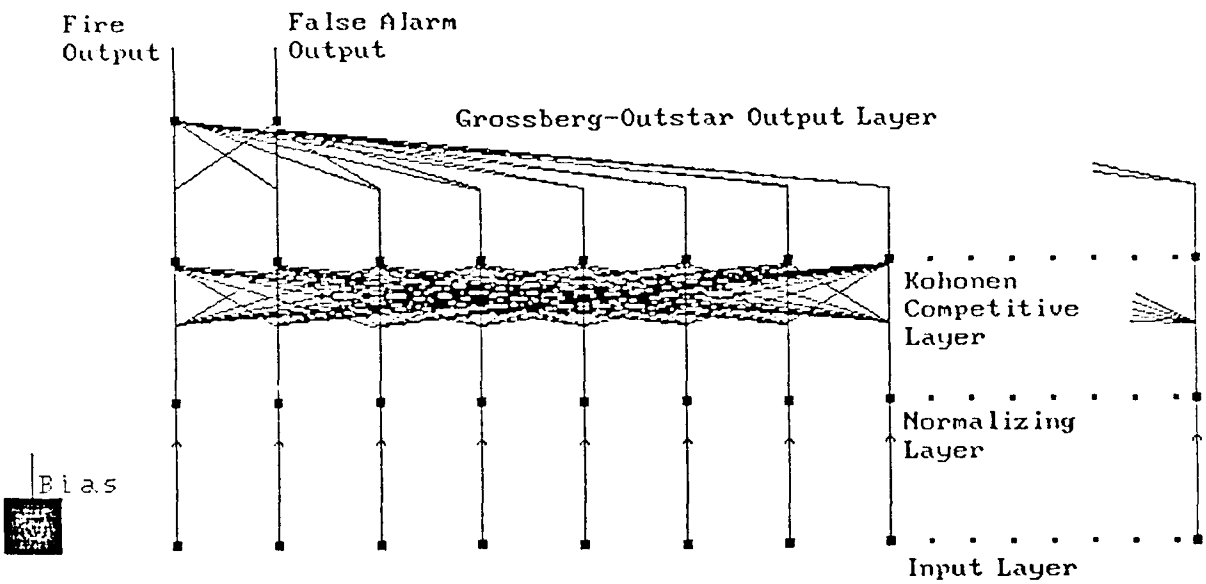


Figure 6. Counter-Propagation Uni-Flow Network Architecture

D. NEURAL NETWORK IMPLEMENTATION

Technical Objective 3, the implementation of the neural network and provision of a user interface, was accomplished with the development of the Phase I neural network architecture. The network structure evolved through three distinct models. Initially, the neural network was implemented with the AI Ware N-Net 210 system as a two layer (no hidden layers) architecture with functional-link expansion of the input. This network was designed to accept 256 hue-value input channels which were "functional link" expanded into over 1200 effective input nodes. This model was designed to detect fires and identify the type of material which was burning. The output layer of the network supported three output channels, indicating the presence or absence of burning wood, paper, or Plexiglass. A high value indicated the combustion of that particular fuel, while multiple high values were manifest if there were several fuels burning. If there were no fires, all outputs would be low.

A second version of this architecture was developed when it was determined that the network size was larger than could be supported by the N-Net 210 system. The second network model which was developed represented a modification of the first model. In this architecture, the number of input channels was reduced to 64 values by averaging the original hue histogram values as groups of four. The 64 input channels were "functional link" expanded to 315 input layer nodes.

After meeting with the Contract Technical Monitor during the Three Month Program Review, the definition of the network analysis function was refined and network implementation efforts converged on a more specific application; namely, hangar fire detection with JP-4 and JP-5 as primary fuel sources. The definition of a more detailed system application provided the basis for the development of a third network architecture using a Neural Works Professional II development system. The third and final Phase I network model is based on counter-propagation with hidden layers and supports 128 input channels with no functional link expansion. Sixty-four of the input channels provide hue histogram information while the other 64 provide saturation histogram information. The output layer supports two output channels corresponding to a fire/no fire indication.

The finalized Phase I system architecture was designed to analyze possible fire regions within an image. Region extraction is accomplished using digital filters for preprocessing analysis of the image for the presence of possible fire regions before presentation to the network. These regions are characterized by high intensity, unique hue and unique saturation spectrums. Several sets of training and test imagery were generated. This imagery was selected to contain flame sources, complex background structures and possible false alarm sources. The training and test imagery was captured using a desktop computer, commercial video digitizing hardware, and software developed for the program effort. The system software, which was written in C, was designed to capture an image, generate HSI histograms and format the HSI data for input to the neural network.

E. NEURAL NETWORK TRAINING

The completion of **Technical Objective 4**, training of the selected neural network with the video flame data, was accomplished through the training of each of the three network models. The data set for the first network had 256 hue-value input data points and was designed to detect various fuel sources. The input data expansion to over 1200 input nodes proved to be too large for full functional-link expansion of the network. The resulting limited expansion architecture was trained by presenting the network with correlated input/output data sets. During the training process, the network self-modified internal node weights to correct output errors using back-propagation-of-errors techniques. The limited architecture of the first model was unable to successfully converge to an acceptable level of accuracy. As training progressed, network accuracy leveled off at approximately 70 percent for a fire/no fire indication.

To address this problem, a second network was developed which represented a modification of the first network and supported a reduced number (64) of input channels with a three channel output. The training files produced for the second network had 64 input values and 3 corresponding output values. The 64 inputs represented a four-group summation reduction of the 256-bin hue histogram. The output fire indicators corresponded to wood, paper, and Plexiglass as fuel sources. Modified 64 element data sets were used to train this second network. Training efforts on the second network evaluated both back-propagation of error techniques and counter-propagation of error methods. This improved network architecture converged at a more acceptable error level with over 90 percent accuracy on fire/no fire decisions and 75 percent accuracy on fuel source classification.

The development of the third and final Phase I neural network model was driven by network optimization efforts which occurred during the completion of **Technical Objective 5**. This third model was designed to address real-world applications as outlined by the Contract Technical Monitor such as hangar fire detection in which primary fuel sources are JP-4 and JP-5 aviation fuel. The final Phase I network architecture, which does not use functional link expansion, is based on a hidden layer model which supports counter-propagation of errors. In view of the intended system application, training and test imagery containing burning JP-4, complex backgrounds and possible false alarm regions was digitized. After training was completed, the final Phase I network demonstrated 100 percent accuracy on the training and test data sets which were generated during Phase I of the program.

F. EVALUATION OF NETWORK ARCHITECTURE, NODES AND INPUT DATA ATTRIBUTES

In order to accomplish **Technical Objective 5**, the evaluation of pixel geometries for compactness and reliability, it was recognized that input data reduction was needed to ensure high speed "real-time" fire detection while minimizing false alarm incidents. In the Phase I system this data reduction is achieved by simple rule criterion filtering to remove all non-flame like pixels before image data is presented to the network for analysis. The "simple rule" criteria which were used to reduce the input data set defined possible "dangerous" fire region characteristics as high intensity, unique hue spectrum and significant growth. If each of these characteristics were present in an image then the image was analyzed by the neural network to ascertain if a region was actually fire or was a false alarm.

Initially, spatial analysis of imagery was based on section by section scans of a rectangular grid which was overlaid on the image. Problems which were encountered with this scanning technique included detection of flame regions which overlap multiple segments and identification of isolated "safe" and "dangerous" fire regions within disassociated segments. To address these problems, a different scanning solution using region ("blob") analysis techniques was developed. Region analysis which uses no set pattern of image division is based on the detection and identification of associated regions in an image. Using this type of analysis, each object in an image becomes an individual segment in the scanning process. As discussed previously, "simple rule" filtering is used to reduce the number of pixels, and thus image regions, which are labeled and analyzed. The filtering process allows areas of interest in an image to be extracted for more detailed analysis. The application of such data reduction techniques make possible the development of a faster, more efficient fire detection system.

Once a region is identified for more detailed neural network analysis, hue and saturation characteristics for that region are determined. The significance of hue information in the identification of fire regions was demonstrated during the completion of earlier technical objectives. To achieve even more accuracy in the fire identification process, saturation information was also provided the neural network. The choice of a combination of hue and saturation histogram information as network input data resulted in a significant increase in network accuracy. The histograms were generated as 256-item linear arrays which were then reduced to 64 items each containing the sum of four consecutive array positions.

G. OPTIMIZATION OF A PROOF-OF-CONCEPT SYSTEM

Technical Objective 6, the optimization of the neural network system to determine efficiency and validity of the system, was approached through the implementation and testing of the Phase I proof-of-concept fire detection system developed in the previous technical objectives. The region characteristics used to identify possible fire regions within an image before a neural network analysis is conducted are: (1) a consistently high intensity, (2) a consistently defined hue bandwidth, and (3) the tendency to expand. The flame characteristic of expansion is used to distinguish "safe" fires from dangerous fires. Dangerous fires tend to expand in a continuous manner, whereas safe fires, after an initial expansion of limited duration, either contract or remain constant. Examples of safe fires include the flame of a welding torch, the flame of a cigarette lighter, flames from the exhaust pipe of a jet, and so on. A block diagram of the proof-of-concept neural network-based fire detection system developed in the Phase I program is shown in Figure 7.

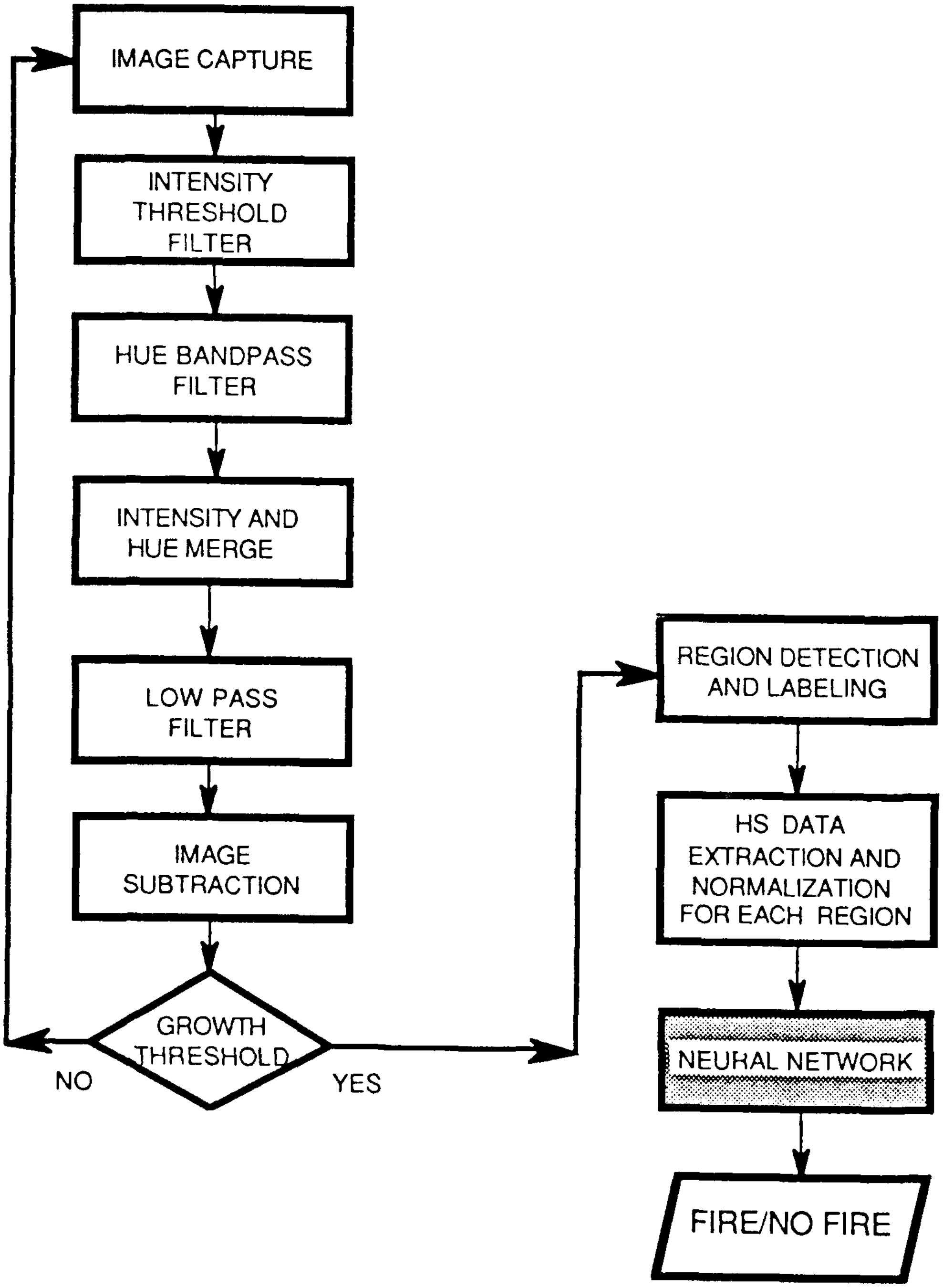


Figure 7. Phase I Proof-of-Concept Fire Detection System

The Phase I system fire detection function is comprised of three subsystems: image capture, image processing and neural network processing. A diagram of the image capture subsystem used in the Phase I program is shown in **Figure 8**. Images are digitized by a Pulnix high resolution CCD camera with RGB output. The RGB signals from the camera are received by a Data Translation DT2871 frame grabber board and are converted into HSI format by frame grabber system hardware. HSI-formatted images are transferred from frame grabber memory to disk by a 25 megahertz 80386 microprocessor-based Gateway 2000 desktop host computer.

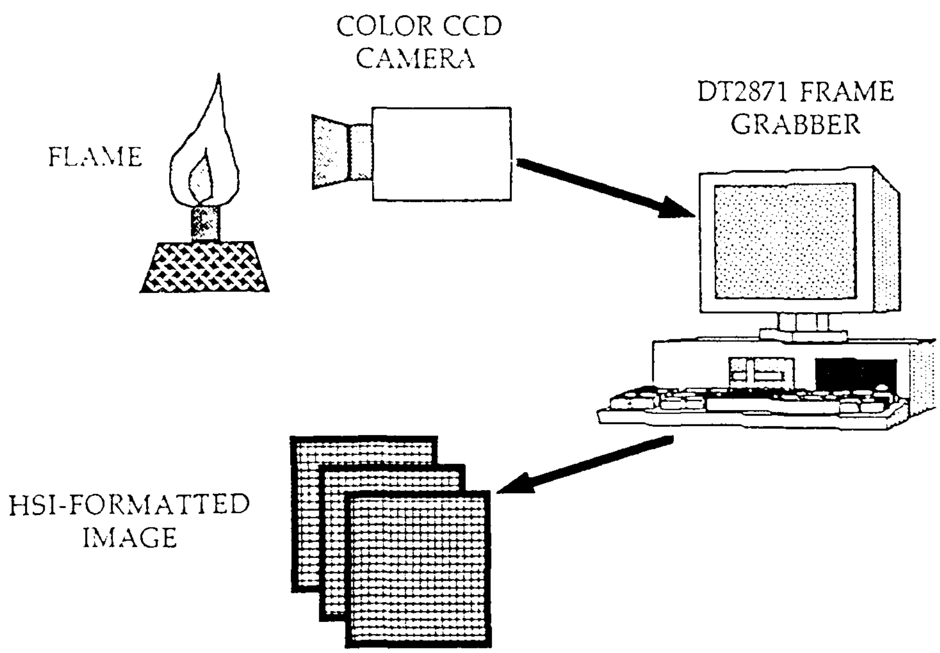


Figure 8. A Diagram of the Image Capture Subsystem

The image processing subsystem consists of eight processing steps. Beginning with the capture of a video frame, let C denote a color digital image of a scene that may or may not contain fire. Mathematically, C is a set of three matrices denoted by C_H, C_S and C_I. Each matrix in C is an n by m matrix containing n rows ranging from 0 to n -1 and m columns ranging from 0 to m -1. The parameters n and m are determined by the limitations of the scanning system utilized and were 480 and 512, respectively, in the experiments performed during the Phase I program. Each element of C_H, C_S and C_I (denoted by $c_H(i,j)$, $c_S(i,j)$ and $c_I(i,j)$, respectively) is an integer ranging from 0 to 2^k -1 where k is an integer greater than 0. The parameter k is the number of bits used to contain an image element and is determined by the limitations of the scanning system utilized. For the Phase I experimentation, a k value of eight (1 byte) was used. The elements of the matrices in C ranged from 0 to 255 and were represented as unsigned integer bytes during computer processing and storage.

The element $c_H(i,j)$ of the matrix C_H represents the hue of the point in the scene scanned corresponding to the (i,j) location in C. As explained in **Technical Objective 1,** hue is the spectral aspect of a color and ranges from red to yellow to green to cyan to blue to magenta and then back to red. The hue scale is a circular scale with red represented by both 0 and 255. The element $c_S(i,j)$ of the matrix C_S represents the saturation of the point in the scene scanned corresponding to the (i,j) location in C. Saturation is the purity of a color in terms of how deep or faded it appears to be and ranges from completely white (0) to completely pure (255). The element $c_I(i,j)$ of the matrix C_I represents the intensity of the point in the scene scanned corresponding to the (i,j) location in C. Intensity is brightness and ranges from completely black (0) to completely white (255). Intermediate levels of intensity are gray level increments between completely black and completely white so that C_I represents the black and white version of the color image C. **Figure 9** shows an example of a C_I matrix that contains regions corresponding to flames. Each ordered triplet $(c_H(i,j), c_S(i,j), c_I(i,j))=c(i,j)$ of C is called a *pixel* of C.

The first processing step, intensity thresholding, locates the pixels in C that have intensity levels equal to the intensity levels of fire. The input of this processing step is C_I. The output is an n by m binary matrix T_I where $t_I(i,j)=1$, if $c_I(i,j)$ is greater than or equal to I_{Min} while $t_I(i,j)=0$, if $c_I(i,j)$ is less than I_{Min}. The parameter I_{Min} is defined to be the lowest intensity value consistently observed for fire, and is a function of the camera saturation setting. In the experiments performed during Phase I, I_{Min} was set to 150. **Figure 10** shows the T_I matrix obtained from the image in **Figure 9** where gray represents the value 1 and white represents the value 0.

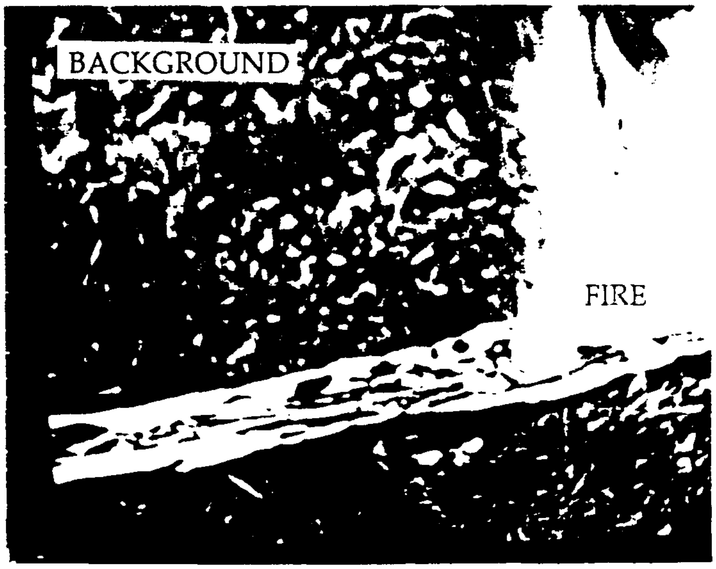


Figure 9. Intensity Representation of Imagery Containing Fire Regions

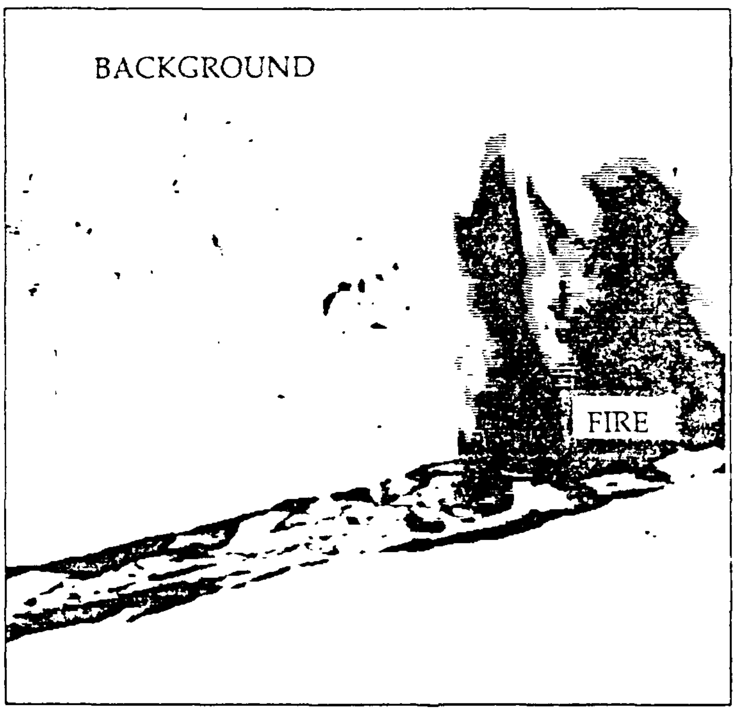


Figure 10. Intensity Thresholded Imagery of Fire Regions

The second processing step, hue thresholding, locates the pixels in C that have hue levels equal to the hue levels of fire. Experimentation has shown that the hue levels of flames fall between 0 (red) and 50 (yellow), and between 200 (magenta) and 255 (red). The inputs of this processing step are C_H and T_I. The output is an n by m binary matrix T_H, where $t_H(i,j)=1$, if $c_H(i,j)$ is either between 0 and 50 or between 200 and 255; otherwise, $t_H(i,j)=0$. **Figure 11** shows the T_H matrix obtained from the image in **Figure 9**, where gray represents the value 1 and white represents the value 0.

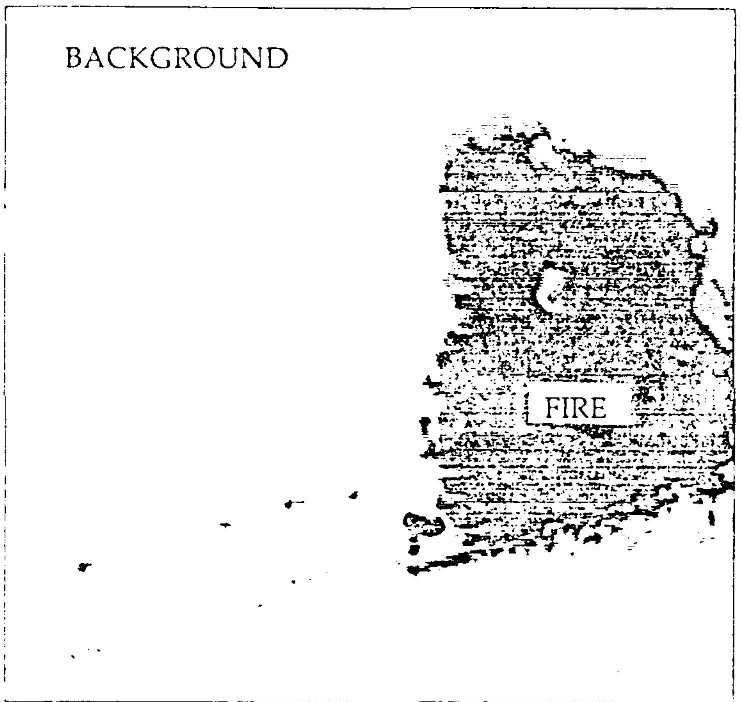


Figure 11. Hue Thresholded Imagery of Fire Regions

The third processing step, merging of thresholded images, performs the logical ANDing of T_I and T_H. This operation is illustrated in **Figure 12**. The output image of this processing step, T, is an n by m binary image where $t(i,j)=1$, if $t_I(i,j)=1$ and $t_H(i,j)=1$; otherwise, $t(i,j)=0$. Thus, $t(i,j)=1$ if the intensity value and the hue value of the pixel at location (i,j) in C are within the intensity and hue ranges, respectively, defined for fire. **Figure 13** shows the T matrix obtained from the image in **Figure 9**, where gray represents the value 1 and white represents the value 0.

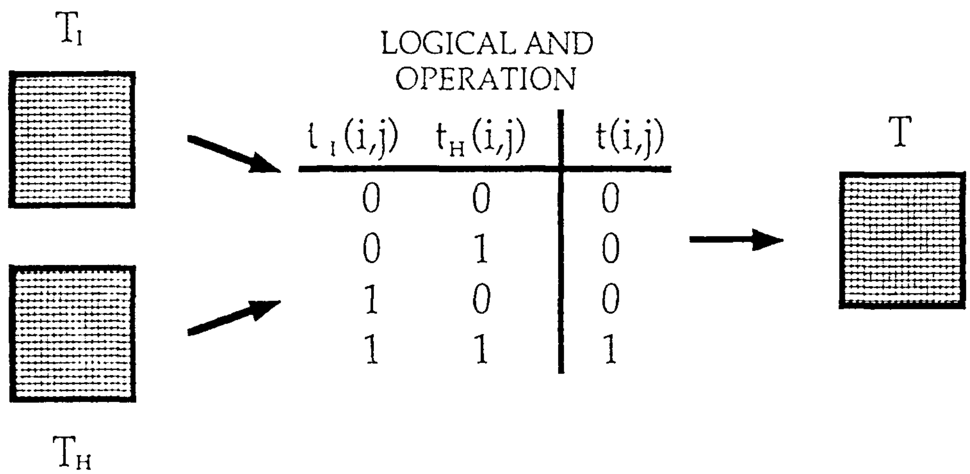


Figure 12. The Logical ANDing Operation of T_I and T_H

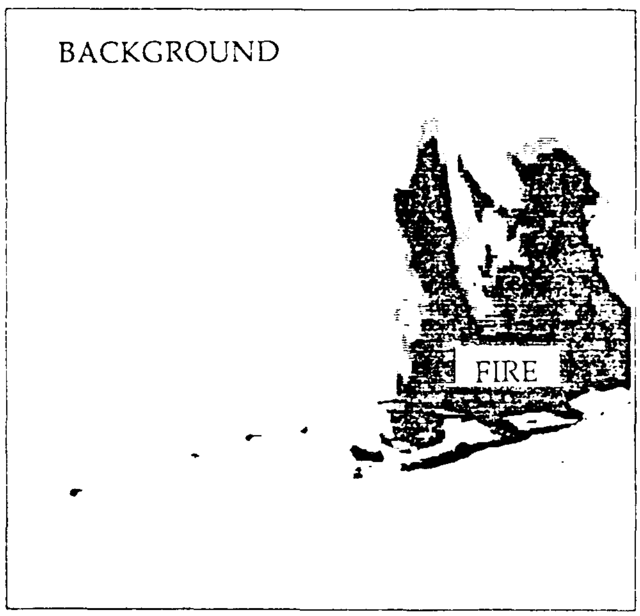


Figure 13. The T Matrix Image Obtained from the Logical ANDing of T_I and T_H

The fourth processing step, low-pass filtering, removes high frequency values from T, i.e. the edges in T are smoothed as shown in **Figure 14**. The purpose of this processing step is to remove high frequency noise caused by fire flicker, since inaccurate determination of fire expansion in the growth analysis processing step has been observed to occur if this noise is unattenuated. In addition, edges of fire regions tend to be semi-transparent and may exhibit corrupted HSI characteristics. The output of this processing step is an n by m binary matrix F, where $f(i,j)=1$, if $t(i-1,j-1) = t(i-1,j) = t(i-1,j+1) = t(i,j-1) = t(i,j) = t(i,j+1) = t(i+1,j-1) = t(i+1,j) = t(i+1,j+1)=1$; otherwise, $f(i,j)=0$. This operation is illustrated in **Figure 15**. **Figure 16** shows the F matrix obtained from the image in **Figure 9**, where gray represents the value 1 and white represents the value 0.

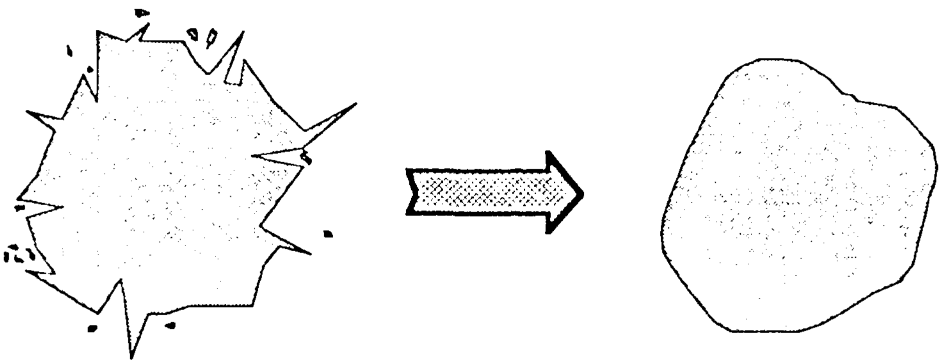


Figure 14. Results of Low Pass Filtering on a Region

$$f(i,j) = 1 \text{ if } \begin{bmatrix} t(i-1,j-1) & t(i-1,j) & t(i-1,j+1) \\ t(i,j-1) & t(i,j) & t(i,j+1) \\ t(i+1,j-1) & t(i+1,j) & t(i+1,j+1) \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$f(i,j) = 0$, otherwise

Figure 15. Low Pass Filtering Operation

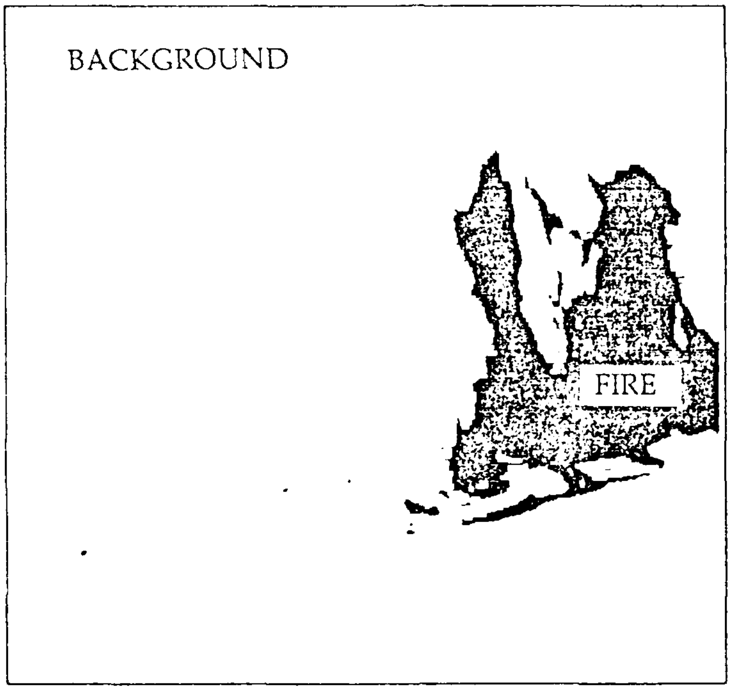


Figure 16. Low Pass Filtered Imagery of Fire Regions

The fifth processing step, image subtraction, subtracts F_t from $F_{t-\Delta t}$ where F_t denotes the F matrix obtained from the image scanned at time t. The term $F_{t-\Delta t}$ denotes the F matrix obtained from the image scanned at time $t - \Delta t$. Here t denotes time (in seconds) and Δt denotes a predetermined increment of time (in seconds) that is limited by the scanning speed of the system utilized. The information obtained in this processing step is required for the growth analysis operation performed in the next processing step. The output of this processing step is an n by m integer matrix S where $s(i,j) = f_{t-\Delta t}(i,j) - f_t(i,j)$. If $f_{t-\Delta t}(i,j)=1$ and $f_t(i,j)=0$, then $s(i,j)=1$ and flame contraction is implied. If $f_{t-\Delta t}(i,j)=0$ and $f_t(i,j)=1$, then $s(i,j)=-1$ and flame expansion is implied. If $f_{t-\Delta t}(i,j) = f_t(i,j)$, then $s(i,j)=0$ and flame constancy is implied. **Figures 17** and **18,** show black and white images scanned at times t and $t - \Delta t$, respectively. **Figure 19** shows the S matrix obtained from the images shown in **Figures 17** and **18** where black represents the value 1 (contraction), gray represents the value -1 (expansion) and white represents the value 0 (constancy).

The sixth processing step, growth decision, determines whether there has been sufficient flame growth in Δt seconds to warrant further analysis of the image scanned at time t. The input of this processing step is S. Let N_p denote the smallest number of 8-connected pixels that can be correctly identified by the neural network as corresponding to flames. The locations of the pixels that are 8-connected to a pixel at location (i,j) are defined to be $(i-1,j-1)$, $(i-1,j)$, $(i-1,j+1)$, $(i,j-1)$, $(i,j+1)$, $(i+1,j-1)$, $(i+1,j)$ and $(i+1,j+1)$. If the number of expansion elements in S is greater than or equal to $0.05 \cdot N_p$ (5 percent of N_p), the image scanned at time t is processed further; otherwise, a new image is scanned at time $t+\Delta t$ and the processing begins again at the first processing step. Thus, the processing of the image scanned at time t is continued, if and only if, a fire growth size greater than or equal to 5 percent of the area of the smallest fire region detectable by the neural network occurs in Δt seconds.

Figure 17. Gray-Scale Intensity Imagery of Scene at Time "t"

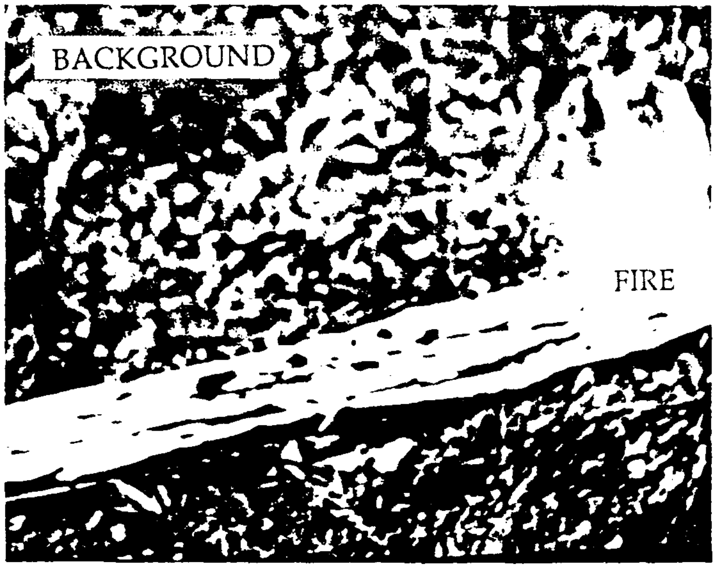


Figure 18. Gray-Scale Intensity Imagery of Scene at Time "t - Δt"

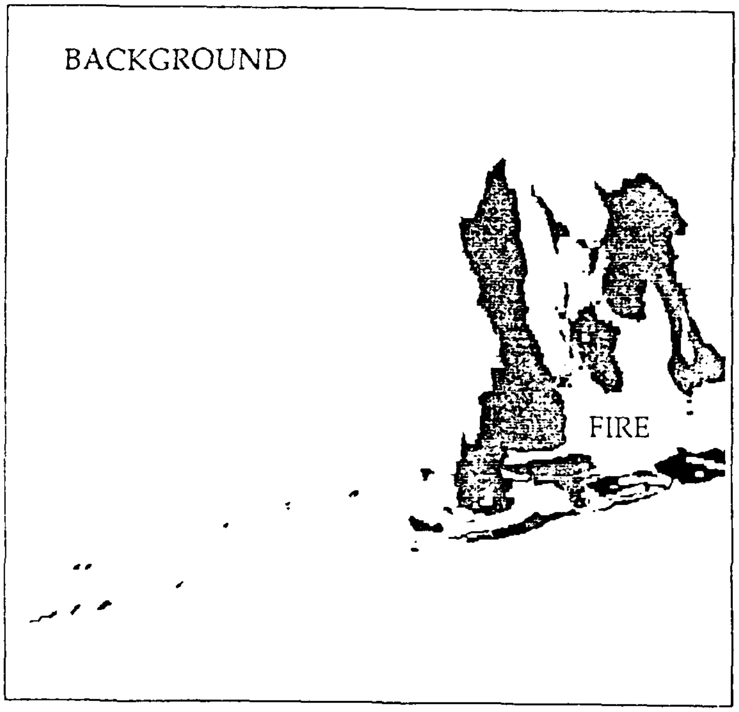


Figure 19. Subtraction Matrix of "t" from "t - Δt" Imagery

The seventh processing step, region detection and labeling, labels the 8-connected regions believed to be fire in the F matrix obtained from the image scanned at time t. The output of this processing step is an n by m integer matrix R where $r(i,j) = r(k,l)$ if $f(i,j)$ and $f(k,l)$ belong to the same 8-connected region; otherwise, $r(i,j)$ does not equal $r(k,l)$. Region labeling is accomplished by first setting the elements in R equal to 0. Let L denote the current region label; initially, $L=0$. Next, a row-by-row and column-by-column scan is performed on F. If $f(i,j)=1$ (possible flame) and $r(i,j)=0$ (unlabeled) then L is incremented and $r(i,j)$ is set equal to L. The elements in F that are equal to 1 and whose corresponding elements in R are 8-connected to at least one element in R equal to L are set equal to L. The row-by-row, column-by-column scan of F is then resumed at location $(i,j+1)$. After the scan of F is completed, the labels of 8-connected regions in R possessing areas smaller than N_p are set equal to 0 since fire regions possessing areas smaller that N_p are undetectable by the neural network. The Phase I neural network was able to detect fire area (N_p) of less than 1,000 pixels which scale to approximately a four foot by four foot fire region at a range of 150 feet. **Figure 20** shows the R matrix obtained from the image shown in **Figure 9** where white represents the value 0 and gray represents all other values.

The eighth and final processing step, histogram extraction, generates the hue and saturation histograms from C for each labeled region defined by R. The inputs of this processing step are C_H, C_S and R. Let H_H and H_S denote the hue and saturation histograms obtained from C_H and C_S, respectively, for a region in R defined by label L. H_H and H_S are real vectors of size 2^k where k is defined in earlier paragraphs in this section. Initially $h_H(i)$ and $h_S(i)$ are set equal to 0 for $i=0,\ldots,2^k-1$. Then for each $r(i,j)=L$, $h_H(a)$ and $h_S(b)$ are incremented where $a = c_H(i,j)$ and $b = c_S(i,j)$. The histograms are then normalized with respect to area by dividing each element of H_H and H_S by N_L where N_L is the number of pixels comprising the region in R defined by label L. Each sum $h_H(i) + h_H(i+1) + h_H(i+2) + h_H(i+3)$ and $h_S(i) + h_S(i+1) + h_S(i+2) + h_S(i+3)$, $i=0,4,8,\ldots,2^k-1$, constitutes an input to the neural network for the region in R defined by label L. Adjacent elements of H_H and H_S are combined in this manner due to the limited number of neural network input nodes available in practical networks. Based on the information provided by the image processing subsystem, the neural network subsystem makes a fire/no fire determination for the region in R defined by label L. This procedure is performed for all L in R (except L =0).

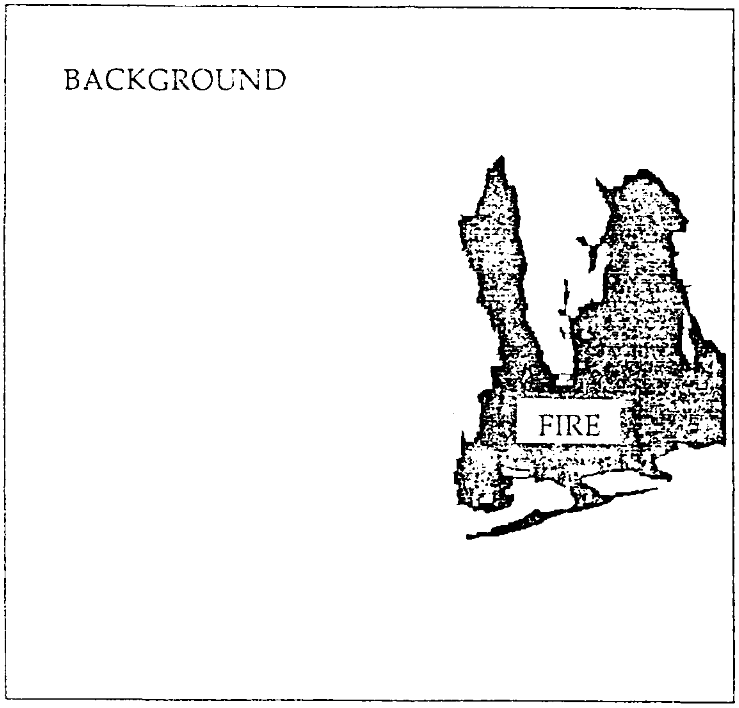


Figure 20. Possible Fire Regions Detected Within Imagery

SECTION III

EXPERIMENTAL RESULTS

This section contains a compilation of the results of the software and hardware development and evaluation conducted to meet the Phase I Technical Objectives. The goal of this program was the development of a Phase I prototype system which demonstrates the feasibility of the development of an artificially intelligent fire detection system using neural network processing techniques. This section describes the results of the Phase I program development effort.

A. EVALUATION OF DIGITIZED VIDEO IMAGERY

The completion of **Technical Objective 1**, the evaluation of machine vision data, resulted in an investigation of the hue, saturation and intensity (HSI) characteristics of digitized imagery of flame regions and false alarm regions. The video data studied consisted of the hue-, saturation- and intensity-level histograms of images scanned under varying lighting conditions. The images which were scanned contained regions corresponding to flames (fueled by JP-4, wood, paper, butane and Plexiglass), direct sunlight, reflected sunlight from glass, reflected sunlight from metal, reflected sunlight from wood, and indoor lights. The hue levels of regions corresponding to flames were found to lie between red (0) and yellow (50) and between magenta (200) and red (255). The intensity levels of regions corresponding to flames were found to lie above 150 at maximum or near-maximum camera saturation settings. The saturation levels of regions corresponding to flames were found to span the entire saturation scale. The curves of hue- and saturation-level histograms of regions corresponding to flames were found to differ substantially in shape from the curves of hue- and saturation-level histograms of regions corresponding to other light-producing phenomena. The curves of intensity-level histograms of regions corresponding to flames and regions corresponding to other light-producing phenomena could not be distinguished.

B. SELECTION OF NEURAL NETWORK PARADIGM

The accomplishment of **Technical Objective 2** involved the identification and acquisition of a neural network paradigm. The completion of this objective resulted in the evolutionary development of three network models. The functional link expansion paradigm which is based on an expansion of the system inputs by generating functional combinations of the original input values and then using these functional values as additional system inputs represents the first network paradigm which was developed during the Phase I program. This model contained no hidden layers and supported back-propagation of errors with over 1200 effective input nodes and three output nodes. The second model which was developed represented a modified version of the first model with 128 input nodes. The third and final network paradigm which was developed supported hidden layers, counter-propagation of errors, 128 input nodes with no functional link expansion and a two node fire/no fire output layer.

C. NEURAL NETWORK IMPLEMENTATION

The completion of **Technical Objective 3**, the implementation of the neural network and provision of a user interface, resulted in the development of the Phase I neural network architecture. The network structure evolved through three distinct advances in paradigm accuracy, efficiency and speed. The initial network model was designed to support a two layer (no hidden layers) architecture with functional-link expansion of the input corresponding to 256 hue value input channels which were expanded into over 1200 effective input nodes. This model was designed to detect fires and identify the type of material which was burning. It was found that the efficiency and speed of this type of paradigm could be enhanced by reducing the complexity of the input layer nodes from over 1200 to 64. This reduced input paradigm was implemented as a second network model.

Meetings with the Contract Technical Monitor resulted in a more detailed definition of the network analysis function and network implementation efforts converged on a more specific application; namely, hangar fire detection with JP-4 and JP-5 as primary fuel sources. The definition of a more detailed system application provided the basis for the development of a third network architecture which could analyze hue and saturation information and provide a fire/no fire output response. During the development of the final Phase I network model, training and test data sets were generated from video imagery containing regions corresponding to flames fueled by JP-4, direct sunlight, reflected sunlight from glass, reflected sunlight from metal, reflected sunlight from wood, and indoor lights.

D. NEURAL NETWORK TRAINING

The completion of **Technical Objective 4**, training of the selected neural network with the video flame data, resulted in the training of each of the three network models. The training data set for the first network had 256 hue histogram bins representing imagery containing flame regions from various fuel sources. The training process used back-propagation of error techniques to modify internal node weights. This first network model was unable to successfully converge to an acceptable level of accuracy. As training progressed, network accuracy leveled off at approximately 70 percent for a fire/no fire indication.

The second network architecture represented a modification of the first network and supported a reduced number (64) of input channels with a three channel output. The training files produced for the second network had 64 hue input values and 3 corresponding output values. The 64 input bins represented a four-group summation reduction of the original 256-bin hue histogram input data used by the first model. The output fire indicators corresponded to wood, paper, and Plexiglass as fuel sources. Training efforts on the second network evaluated both back-propagation of error techniques and counter-propagation of error methods. This improved network architecture converged at a more acceptable error level with over 90 percent accuracy on fire/no fire decisions and 75 percent accuracy on fuel source classification.

The third and final Phase I network model was designed to address real-world applications as outlined by the Contract Technical Monitor such as hangar fire detection in which primary fuel sources are JP-4 and JP-5 aviation fuel. The final Phase I network architecture is based on a hidden layer model which supports counter-propagation of errors. In view of the intended system application, training and test imagery containing burning JP-4, complex backgrounds and possible false alarm regions was digitized. After training was completed, the final Phase I network demonstrated 100 percent accuracy for fire/no fire indications.

E. EVALUATION OF NETWORK ARCHITECTURE, NODES AND INPUT DATA ATTRIBUTES

The completion of **Technical Objective 5**, the evaluation of pixel geometries for compactness and reliability, resulted in the development of pre-network processing digital filtering algorithms for data reduction to ensure high speed "real-time" fire detection while minimizing false alarm incidents. The result of this effort was the implementation of a series of simple rule criterion filters to remove all non-flame like pixels before image data is presented to the network for analysis. The "simple rule" criteria which were used to reduce the input data set defined possible "dangerous" fire region characteristics as high intensity, unique hue spectrum and significant growth.

If each of these characteristics were present in an image then regions within the image were analyzed by the neural network to ascertain if a region was actually fire or was a false alarm. This spatial scanning process which was initially based on uniform grid segments was later changed to a different scanning solution using region ("blob") analysis techniques. Problems which were encountered with grid scanning included detection of multiple segment flame regions and identification of isolated regions within disassociated segments. Using region analysis, each associated object in an image becomes an individual segment in the scanning process. "Simple rule" filtering is used to reduce the number of pixels, and thus image regions, which are labeled and analyzed. The application of the previously discussed data reduction techniques resulted in the development of a faster, more efficient Phase I system. The final Phase I network was trained to analyze both hue and saturation characteristics in each region of interest. The choice of a combination of hue and saturation histogram information as network input data resulted in a significant increase in network accuracy.

F. OPTIMIZATION OF A PROOF-OF-CONCEPT SYSTEM

The accomplishment of **Technical Objective 6**, the optimization of the neural network system to determine efficiency and validity of the system, resulted in the implementation and testing of the Phase I proof-of-concept fire detection system developed in Technical Objectives 1 through 5. Work conducted during the Phase I program resulted in a highly accurate neural network architecture. The final Phase I neural network was trained to recognize expanding fire regions within an image using 137 training data sets consisting of 96 fire region sets and 41 false alarm region sets. These data sets included flames fueled by JP-4, direct sunlight, reflected sunlight from glass, reflected sunlight from metal, reflected sunlight from wood, and indoor lights. After training was completed, the network was presented 23 test data sets containing 17 fire regions and 6 false alarm regions. The network demonstrated 100 percent accuracy with the training data sets and was also 100 percent accurate with the test data sets. The system was also able to demonstrate reliable and repeatable detection of fire regions scaled to 4 by 4 feet at a range of 150 feet.

SECTION IV

CONCLUSIONS, TECHNICAL FEASIBILITY AND RECOMMENDATION

In this section of the report, major conclusions are presented based on the results of the Phase I project and information available during the study. These conclusions are followed by a discussion of the technical feasibility of each objective and the degree to which each objective has been met. Finally, the potential applications of the program are discussed with regard to use by the Federal Government and in potential commercial applications.

A. CONCLUSIONS

Based on the results presented in this report and other results obtained during this study, it is possible to draw the following conclusions.

- Experimental results suggest that HSI video format is superior to RGB video format in this particular application. The use of HSI format imagery reduces processing complexity and simplifies the interpretation of region characteristics.

- Regions corresponding to flames in a video image can be segmented from the rest of the image based on a thresholding scheme involving the hue- and intensity-level histograms of the entire image. The use of threshold filtering reduces the computational overhead required by video frame analysis techniques.

- The profiles of hue- and saturation-level histograms of regions corresponding to flames can differ significantly in shape from the curves of hue- and saturation-level histograms of regions corresponding to other light-producing phenomena while the profiles of intensity-level histograms of regions corresponding to flames and regions corresponding to other light-producing phenomena could not be easily distinguished. These findings indicate that there exists the possibility of using hue and saturation information in machine vision imagery to detect the presence of flame in a complex false alarm background.

- For a given application, optimization of the neural network processing architecture by restructuring input layers, by adding hidden layers and by selecting error propagation techniques can contribute significantly to improved system performance. For hangar fire detection applications, it was found that an architecture which can process hue and saturation histogram data using hidden layers and counter-propagation of errors provides a highly accurate fire detection capability.

- Experimental results suggest that the neural network-based system developed during the Phase I program can correctly extract regions corresponding to flames (fueled by JP-4) as well as regions corresponding to other light-producing phenomena and can accurately identify each region as a "safe" fire, a "dangerous" fire or a false alarm incident.

- Experimental work conducted during the Phase I program indicates that a neural network-based fire detection system which uses machine vision techniques is feasible provided the software algorithms developed for the Phase I proof-of-concept system can be successfully translated into high speed hardware. The likelihood of such a software-to-hardware translation being successful is high as high speed image processing hardware is readily available as off-the-shelf components.

B. TECHNICAL FEASIBILITY AND EXTENT TO WHICH PHASE I OBJECTIVES HAVE BEEN MET

This discussion of technical feasibility considers the Phase I program objectives and technical findings and the state of the art as reflected in the literature.

- **Technical Objective 1** was achieved by evaluating the characteristics of visible spectrum machine vision imagery of fire regions in complex false alarm backgrounds. It was shown that fire regions can be differentiated from false alarm regions using the unique characteristics of region hue and saturation histogram profiles.

- **Technical Objective 2** was achieved by the selection of an optimal neural network paradigm for use in the Phase I proof-of-concept system. The selection process began with a functional link expansion architecture which supported back-propagation of errors, 1200 effective input nodes and no hidden layers. As the program progressed, the number of input nodes was reduced and the architecture was modified to support hidden layers and counter-propagation of errors.

- **Technical Objective 3** was achieved through the implementation of the neural network architectures which were selected in the previous technical objective. The development of each of the three architectures was accomplished successfully with full implementations of the second and third models and a limited implementation of the first model which supported 1200 input nodes and suffered some performance degradation due to hardware memory limitations.

- **Technical Objective 4** was achieved through the training of the neural network architectures implemented in the previous technical objective. Training was accomplished using training data sets generated from fire, background and false alarm imagery. The accuracy of the network with various numbers of inputs was observed and the results of neural network architecture modifications were compared.

- **Technical Objective 5** was achieved with the evaluation and optimization of various input data geometries. Input optimization efforts included the development of digital preprocessing filters and the determination of which input and node configurations ensured maximum operating efficiency and speed.

- In order to achieve **Technical Objective 6**, the Phase I proof-of-concept neural network system was tested and refined for optimal performance in hangar fire detection applications. Optimization efforts included the improvement of overall system module architecture, enhancement of the preprocessing digital filter algorithms, optimization of network input layer structure and the addition of hidden layers within the neural network architecture. Phase I test results indicate that the development of a neural network-based fire detection system is feasible.

Each of the specified technical objectives for the Phase I project was achieved, indicating the feasibility of the technical program to develop a neural network-based fire detection system using machine vision techniques. In conclusion, the Phase I program has indicated that the development of such a system is feasible and technically practical.

C. RECOMMENDATION

1. Potential Use by the Federal Government

The neural network fire detection system being developed by this program can be used by all branches of the Federal Government. This system, which is based on a trainable neural network, is readily adaptable to numerous detection environments and can find immediate use in any application requiring a fire detection system. It is envisioned that the system would be installed in high risk areas where high value assets and flammable materials present the potential for highly destructive fires. The completion of Phase II of this program, which is funded by the U.S. Air Force, would result in a fieldable fire detection system capable of immediate use in aircraft hangars, ammunition depots and other high-risk, high value installations.

2. Potential Commercial Applications

Commercial application of the fire detection system being developed by this program will probably occur initially in industry where flammable materials and ignition sources are often in close proximity. In such cases, fire can represent a significant threat. The system could also be used to protect [illegible] facilities such as hospitals, where a fire could cause a critical disruption of medical services, or nuclear power plants, where a fire could result in catastrophic environmental damage. Since the system is automated, applications might also include monitoring of remote installations where more conventional manual fire detection and suppression methods are impractical or unavailable. Other applications outside of fire detection can be found in science where the system can be used for analysis of chemical processes or in industry where the system could monitor manufacturing processes.

3. Follow-On Funding Commitment

A follow-on funding commitment from Venture Resources, Inc. for Phase III commercialization of the neural network-based fire detection system developed under Phase II of the program has been arranged.

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