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A HIERARCHICAL DATA STRUCTURE REPRESENTATION FOR FUSING MULTISENSOR INFORMATION

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ABSTRACT

A major problem with MultiSensor Information Fusion (MSIF) is establishing the level of processing at which information should be fused. Current methodologies, whether based on fusion at the data element, segment/feature, or symbolic levels, are each inadequate for robust MSIF. Data-element fusion has problems with coregistration. Attempts to fuse information using the features of segmented data relies on a presumed similarity between the segmentation characteristics of each data stream. Symbolic-level fusion requires too much advance processing (including object identification) to be useful.

MSIF systems need to operate in real-time, must perform fusion using a variety of sensor types, and should be effective across a wide range of operating conditions or deployment environments.

We address this problem through developing a new representation level which facilitates matching and information fusion. The Hierarchical Data Structure (HDS) representation, created using a multilayer, cooperative/competitive neural network, meets this need. The HDS is an intermediate representation between the raw or smoothed data stream and symbolic interpretation of the data. It represents the structural organization of the data. Fused HDSs will incorporate information from multiple sensors. Their knowledge-rich structure aids top-down scene interpretation via both model matching and knowledge-based region interpretation.

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1.0 MULTISOURCE INFORMATION FUSION (MSIF): A SIGNIFICANT NEED, A CHALLENGING PROBLEM

Sensor data fusion has the potential to offer significant performance improvements in a variety of systems. Today's sensor fusion technology is no longer a "black box." The VLSI integrated circuit technology makes it possible to develop a new standard for use in the field. By integrating information from multiple sensors, we can reduce the reliance on any single sensor or sensor type. Thus, we can achieve increased system performance even under the loss of individual sensor performance.

MultiSensor Information Fusion (MSIF) systems should be robust, real-time, and fault-tolerant. There are several fundamental issues which must be addressed and understood before any technology-based consituency will fully support sensor data fusion. These issues are:

- o What to fuse: Focusing attention;
- o When to fuse: Selecting levels for fusion,
- o Where to fuse: Designing system architectures, and
- o How to fuse: Selecting appropriate methodologies.

We focus on selecting the appropriate representation level, and introduce a novel "level" for fusing data information. By using this new "structural representation level," we show that many of the problems that have been major difficulties with previous fusion technologies can be overcome. New technologies, such as neural networks applied to structural organization, make these developments possible.

2.0 WHEN TO FUSE: SELECTING AN APPROPRIATE REPRESENTATION LEVEL

If we have temporally-varying, single-valued data streams from two or more sensors, the most significant questions we can ask are:

- o At what levels of representation (or single-sensor processing) should the information from two or more sensors be combined?

- o Once appropriate representation level(s) for fusion have been determined, how should the information actually be combined?

The reason that these issues are the most important is that they define the nature of the fusion task. Previous work in sensor fusion has met with severe limitations because the representation level has not been adequate for the fusion task. If we can select the right representation level for fusion, then other issues (such as finding a way to focus attention) will fall into place. For this reason, we concentrate in this paper on the issue of selecting an appropriate representation level for sensor data fusion.

The levels which have been proposed thus far are:

* Sensor data level fusion,
* Segment/feature level fusion, and
* Symbolic information fusion.

Only a few researchers seem to have identified the "level of abstraction" as a key issue in MSIF. Tom Rearick [1987 (a) & (b)] is one of those few. His comments are particularly useful, since he is concentrating on image fusion for autonomous landing and related issues for high-performance aircraft. Rearick's focus is on MSIF for vision-type sensors, but his comments have greater generality. He says [1987(a)]:

> "Since no single electro-optic sensor is optimal under all weather and illumination conditions, one is left with the option of fusing image data from multiple sensors...In addition to imaging sensors, one would like to fuse visual information from other sources such as stored databases, radar warning receivers, navigation computers, etc."

We address the issue of "where" to fuse data by considering the level of representation at which fusion should occur.

2.1 SENSOR DATA LEVEL FUSION

Some researchers propose fusing information directly at the sensor level; that is, direct data fusion. This approach is common in multispectral fusion applications [e.g. Evans & Stromberg, 1983; Welch & Ehlers, 1987]. There are a lot of problems with this approach, beginning with problems of coregistration. If the data streams are taken from similar sensors, and are taken from the same locations, then data-level fusion is feasible. Even then, there is some question as to what each "new" data element value (resulting from fusion of data elements from two or more sensors) actually <u>means</u>. If the sensors are from different locations, or if they have very different response characteristics, then this approach will not work.

2.2 FEATURE LEVEL FUSION

Most researchers doing MSIF favor fusing segments or "events" extracted from temporally-varying data streams. This whole approach is based on the premise that a segment in one data stream can be matched on a one-to-one basis with a corresponding segment in a different stream [Dietz et al, 1988]. There are several difficulties with this approach.

First, segments and features from different sensors may not match. This may be due to the intrinsic nature of what each sensor reponds to, or it may be due to differences in the way the segmentation algorithms work. Other differences may be due to temporal or spatial dislocations in the reponses of sensors.

Second, the feature level itself may not be a useful level for information fusion. There is no potential at the feature level itself to represent patterns of features, whether spatial, temporal, or spatio-temporal. It may be that the information needed for accurate fusion resides at a pattern level which is one level more abstract than feature extraction.

Third, many approaches to sensor fusion at this level are really attempts to produce a Bayesian-type of decision about the nature of the observed event. [See, e.g., Goodman, 1987; Chang et al., 1986; Bowman & Murphy, 1981, Luo et al, 1988]. This approach confuses two tasks together; that of sensor data fusion and sensor data interpretation. Bayesian-based methods for decision-making may not be appropriate, especially when the sensor data evolves into complex patterns which require higher-level descriptions [Nasburg & Moravec, 1984; Gallant, 1988; Garvey, 1981].

During the early 1980's, researchers had good reasons for advocating AI/expert system approaches to the sensor fusion problem [Drazovich, 1983]. However, Drazovich and other AI advocates have ignored the very real problems which would be encountered in attempts to use rule-based systems in real-time applications scenarios [Garvey et al.; 1981, Gupta & Ali, 1988].

2.3 SYMBOLIC LEVEL FUSION

Rearick recommends that only "salient objects" be fused and represented in the final MSIF output. These salient objects can be found by using using gyxels, an intermediate representation level for parts of segmented regions in images. In Rearick's approach, a "salient object" has not necessarily been identified in terms of what it is; it has simply been identified as a distinct unit from its surround, and has passed some rule-based tests that examine its features. This is similar to the "target-track" level of fusion of many other researchers. "Target-tracks" can be output directly from certain sensor processors, and contain information such as kinematic estimates (e.g. range azimuth, elevation, velocities), as well as possible ID estimates (generally based on Bayesian PDFs) [Bowman, 1985]. This level of fusion is appropriate so long as the objects to be identified are discrete (as in targets), and can be fully specified by a feature list for each target coming from each sensor.

However, a problem with fusion at the symbolic level is that it presumes that certain amount of interpretation of data from each sensor has already been done. This is contrary to the purported goal of MSIF, in which data from multiple sensors is used to create a symbolic interpretation. Also, an expert system approach to evaluate each sensor track would not be feasible in real-time scenarios. Thus, we see that each of the representation levels currently in use has inadequacies for MSIF.

3.0 BIOLOGICAL MULTISOURCE INFORMATION FUSION SYSTEMS SERVE AS INSPIRING MODELS

The human brain is capable of addressing problems such as "what, when, where and how" data fusion should occur. The nervous system functions by integrating different types of information, controlling what data is fused, resolving spatial discontinuities, integrating views from different angles, and fusing data from different sensors. In the brain, sensory data is channeled from a bed or network of neurons called a nucleus to the next network. Each network processes or refines the data into more meaningful or abstracted concepts. The result is passed on to higher levels of the brain for further processing. Conceptually organized sensory fusion begins to occur as information is passed from one cortical area to another [Churchland, 1986].

In human visual processing, features such as color, movement, edges and orientation result from neuronal activity in the eyes, the lateral geniculate nuclei, and the primary visual cortex [Churchland & Sejnowski, 1988]. Obviously, these features are not meaningful in themselves. To be meaningful, considerable activity at the cortical level is required. At each cortical step, the visual information is processed, associated, or fused with information from other sensors.

By the time the multisensory-fused information gets to the parietal cortex, the object has been located in the visual field. In the parietal cortex, the object becomes fused or associated with attentional importance [Wise & Desimone, 1988].

Interestingly, identification of the object is not involved with the parietal cortex. It is in the temporal associative cortex where fusion or association with object identification occurs. This suggests that meaning is the result of association or fusion of neural activities from different areas.

There are two uses for sensory information. One is nonspecific or motivational in nature and is used to activate or alert the brain to the new activity. Much of this work is done in the brain stem's reticular activation system. The nature of this information is not specifically meaningful but is used as a general motivation. It is fused with sensory features in the cortex to help provide motivation for attention and movement.

The other use of sensory information is specific in nature. Information is moved from one layer (ie., nucleus) of networks to the next. Ultimately, the information is processed by the cortex. Here the raw data has been featurized so there is some meaning. Meaning at this level consists of movement detection, color or edge detection. While this information is important, it is also fundamental. Little high level conceptual meaning is evident at this point. Principally, the sensory processing is restricted to columnar organization with little fusion.

4.0 NEW APPROACH TO MSIF: FUSING DATA STRUCTURES

We have developed a robust, generic, and powerful approach to MSIF that works by using a new representation level for fusion. This new representation level is called a Hierarchical Data Structure (HDS). The power of our HDS is based upon segment clustering done by neural network technology. Our neural network technology uses a multilayer, cooperative/competitive paradigm [Minsky & Maren, 1989; Maren et al., 1988]. This technology draws upon neuroscience principles and allows for discrimination of significant events from background, noise, or clutter.

The multilayer architecture allows the system to identify the most "perceptually salient" regions in an image or temporal data stream. This capability could be combined with a "novelty detector" and an adaptive filter to focus attention on meaningful objects. This approach draws inspiration from the biological models which we discussed earlier.

The current HDS process completes the formation of an HDS as each discernable sequence of temporal events occurs. These "events" are portions of the data stream which can be discerned from and segmented from a background value. The exact nature of the events, and the segmentation to extract events, depends on the type of sensor data being monitored.

The HDS method clusters together the "most related" events. Our current HDS system creates clusters between nearest-neighbors of temporally-occuring events. We are investigating various metrics which define the sense of "most related" events, but are viewing this process as analogous to our Hierarchical Scene Structure (HSS) method [Maren et al, 1989; Minsky & Maren, 1989; Maren et al., 1988] for creating clusters from the perceptually salient image regions.

Because clusters are formed from temporally-related events, it is possible to begin cluster structure analysis as soon as distinctive clusters of events are extracted. Further, knowledge-based intepretation can be invoked to search for expected cluster correlations as soon as hypotheses are made.

In multisensor fusion applications, the output of different sensors, or of sensors in different locations, could be processed locally by the HDS paradigm. Novel or perceptually salient events would be identified by each HDS processing system. These novel or salient events would appear as distinct clusters in the HDSs created from each sensor output.

Different sensors will produce data streams which have different types of perceptually salient features. For example, a single phenomenon will cause different responses in temperature and pressure sensors. If distinctive clusters of events can be identified in similar time periods in different data streams, then these clusters can be fused. Fusion will proceed top-down, and focus attention on matching novel or salient clusters first.

This will facilitate real-time operation. This fusion could be accomplished by modifying the current HSS paradigm as described in Minsky & Maren [1989]. Our neural network HDS system can use modifiable weights to learn to identify certain types of high-priority distinctive groupings, such as would occur with specific fault states. A connectionist system could then perform intelligent correlation with stored decision points and models. We anticipate that our HDS approach can be a basis for fusing temporal information, such as is found in seismic or sonar signals.

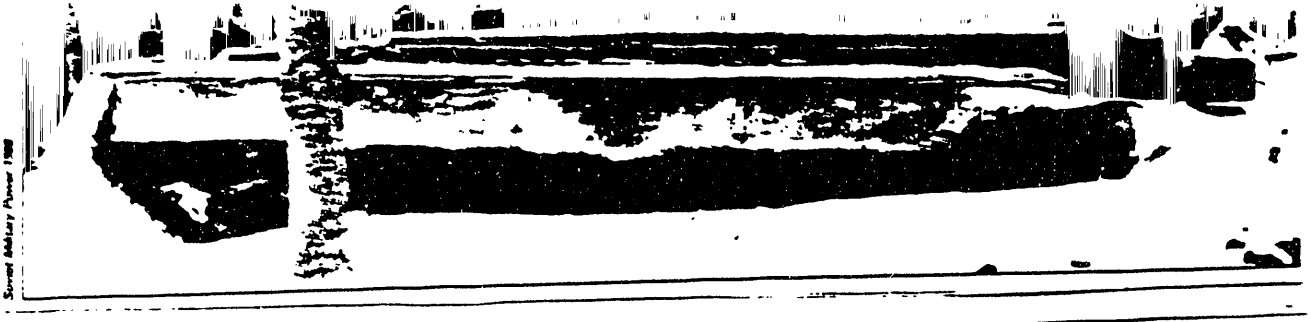
4.1 HIERARCHICAL DATA STRUCTURES REPRESENT THE STRUCTURAL ORGANIZATION OF SEGMENTED EVENTS

We are using Hierarchical Data Structures (HDSs) to structure the segmented events in time-varying signals. We illustrate the HDS approach by describing first how it has evolved from the Hierarchical Scene Structure (HSS) approach. The HSS approach was created as a means of representing the perceptual organization of segmented images.

The primary advantage of using an HSS is that image information is represented in a structured manner. The HSS explicitly encodes valuable high-level information. This high-level information includes the relationships between the segmented regions in an image. This relationship information, including such "perceptual features" as proximity between segments, similarity of intensity or amplitude, and other features, may be valuable in both characterizing the nature of a structured cluster of segments, and in facilitating matches between structures.

In these Hierarchical Structures, the "top node" of the structure contains information about the entire structure, such as its total size, average intensity or amplitude, and other features which describe globally the entire set of segments which make up the structure. Lower-level branch nodes similarly contain information about all nodes subordinant to them. Thus, by examining only the top layers of a structure, it is possible to extract a great deal of information about the structure and its components.

We illustrate the usefulness of the HSS representation in Figures 1 and 2. Figure 1(a) shows an image of a Soviet tank in a forest. Figure 1(b) shows a stylized segmented image of such a tank. In the stylized example, as in the original image, the body, tread, and gun barrel of the tank are split into two components each by the presence of an obscuring tree. This would present a problem to any interpretation system, as it would be difficult to identify the tank from its component segments.



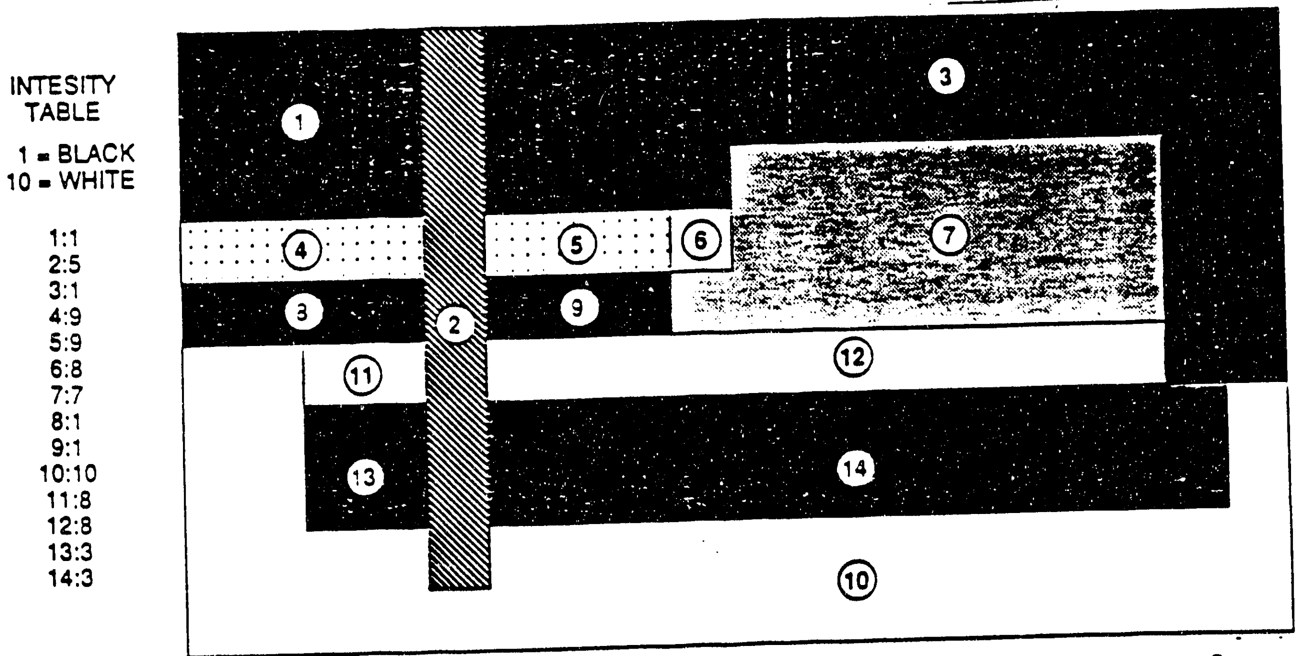


Figure 1. (a) Image of a Soviet tank in a forest, taken from Soviet Military Power (1988). (b) Stylized segmented version of the tree and tank, using a large-pixel synthetic image.

Figure 2(a) shows a Hierarchical Scene Structure created from data corresponding to the segmented tank in Figure 1(b). This HSS was created using a multilayer cooperative/competitive network, which is fully described in [Minsky & Maren, 1989]. An earlier cooperative/competive network for performing this type of region grouping was described in [Maren, Minsky, & Ali, 1988].

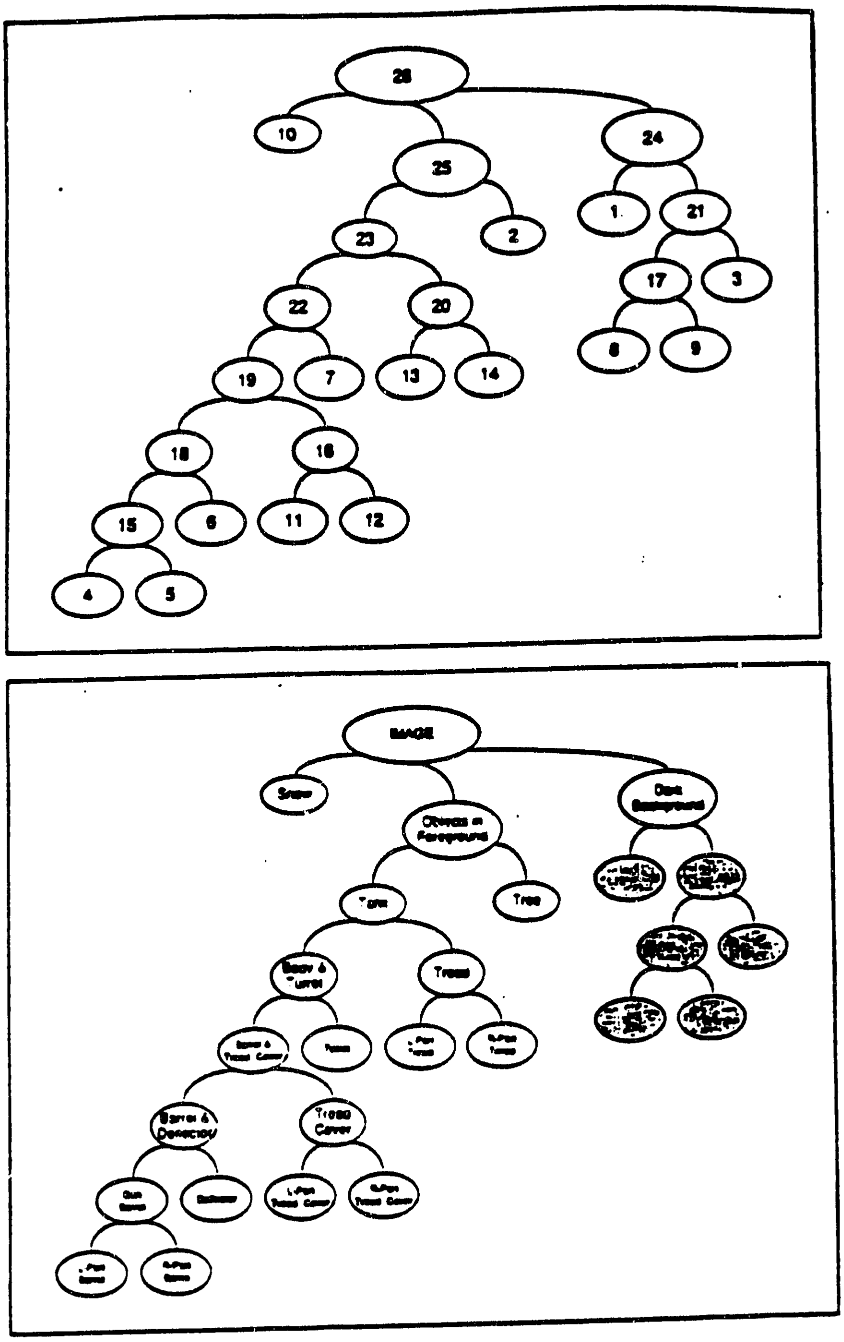


Figure 2 (a) Hierarchical Scene Structure created using perceptual relations calculated between segments shown in Figure 1(a). (b) A knowledge-based system could traverse the HSS and identify major components using both perceptual features and segment-descriptive features, both of which are stored in the HSS. For details, see [Minsky & Maren, 1989; Maren & Ali, 1988, & Maren et al., 1988].

A knowledge-based system could interpret the structure shown in Figure 2(a) to yield interpretation of both the objects and the different parts of the objects, as shown in Figure 2(b). There are two ways in which a knowledge-based system could perform this interpretation. These methods correspond to object model matching and knowledge-based region interpretation. Both approaches rely on the fact that every branch node in an HSS contains information that describes to aggregate properties of all nodes which descend from that branch. Thus, the properties of a branch node can be used to generate tentative object matches or hypotheses about the entire group of regions denoted by that node.

4.2 MULTISOURCE HIERARCHICAL DATA STRUCTURES ARE A ROBUST WAY TO REPRESENT FUSED INFORMATION

When temporal data streams contain events, and the "pattern" of those events is important, then the best approach to multisensor data fusion should take the pattern of events into account. Under these circumstances, our approach to fusing multisource data streams is to use an adaptation of the method we have devised for fusing images. This approach builds on our previous work which represents the structure of each image in terms of a Hierarchical Scene Structure.

Each HSS represents the perceptual organization of a segmented scene. By fusing the HSSs made from different images, we can create a new, information-rich Multisource Hierarchical Scene Structure (MHSS). This structure captures high-confidence components (image segments) from multiple sources, along with knowledge of significant relationships between components, features describing them, and confidence measures. This structured representation is amenable to top-down image analysis.

The HSS approach, when modified to yield the HDS approach, can operate on data such as shown in Figure 3.

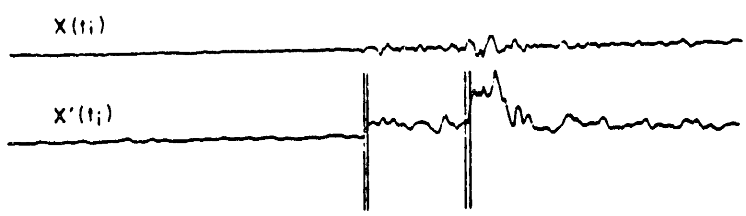


Figure 3. P and S waves from two types of seismic events. (Figure adapted from McEvilly and Majer [1982]). By fusing seismic readings from multiple sensors, it will be possible to obtain a better discrimination of the type of event which caused the seismic disturbance.

The representation levels for an MSIF system are shown in Figure 4. There are two new levels in this system; an HSS (or HDS) level for each sensor, and a fusion level, occuring just above the HSS (HDS) level, to represent the Multisensor-fused Hierarchical Data Structure.

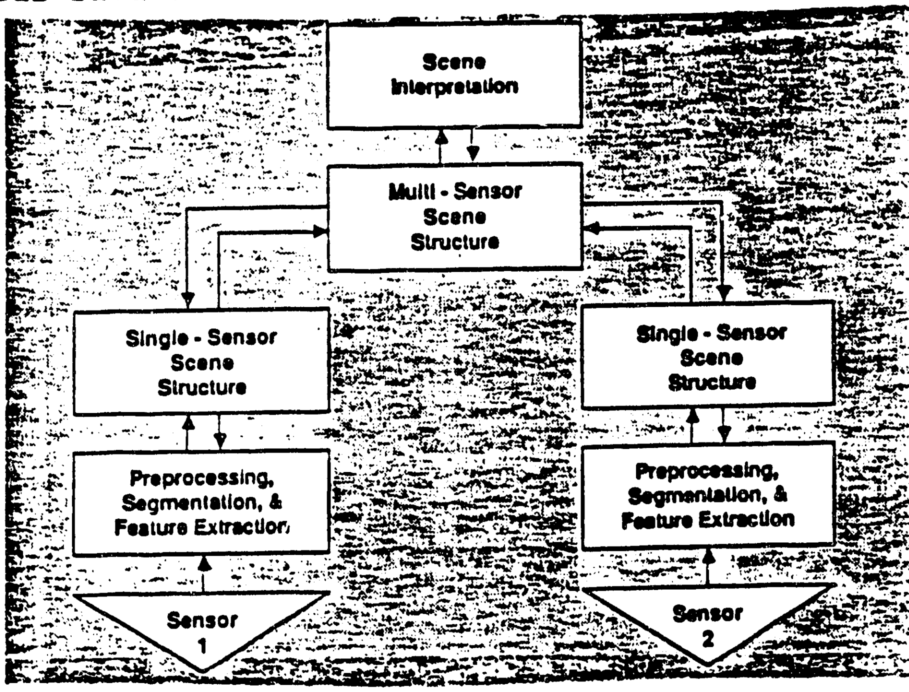


Figure 4. Major representation levels for multisensor information fusion system.

Hierarchical Data (or Scene) Structures, created from each of the input images or data streams, are an appropriate starting point for MSIF because of two factors. First, Hierarchical Data Structures contain unique perceptually-based information (e.g., proximity, similarities) which can be invaluable in matching sets of segments from one image or data stream to sets of segments from another source.

Second, the unique encoding of Hierarchical Data Structures facilitates rapid identification of significant and/or strongly differentiated areas of interest in each image. The fusion process begins with these significant areas, enhancing the probability of a useful match and concentrating processing power on those groups of regions or data segments which are most perceptually distinctive or significant.

Figure 5 shows how single-sensor Hierarchical Scene Structures can be used to provide a basis for fusing multisensor images. Unlike feature-mapping approaches, the fusion here takes place at the scene structure representation level. Stylized visible and IR images in Figures 5(a) and (b) each yield a HSS, shown in Figures 5(c) and 5(d). Fusion occures by matching and merging the single-sensor HSS's in Figure 5(e). This high-confidence MHSS provides a robust basis for scene interpretation, as illustrated in Figure 5(f).

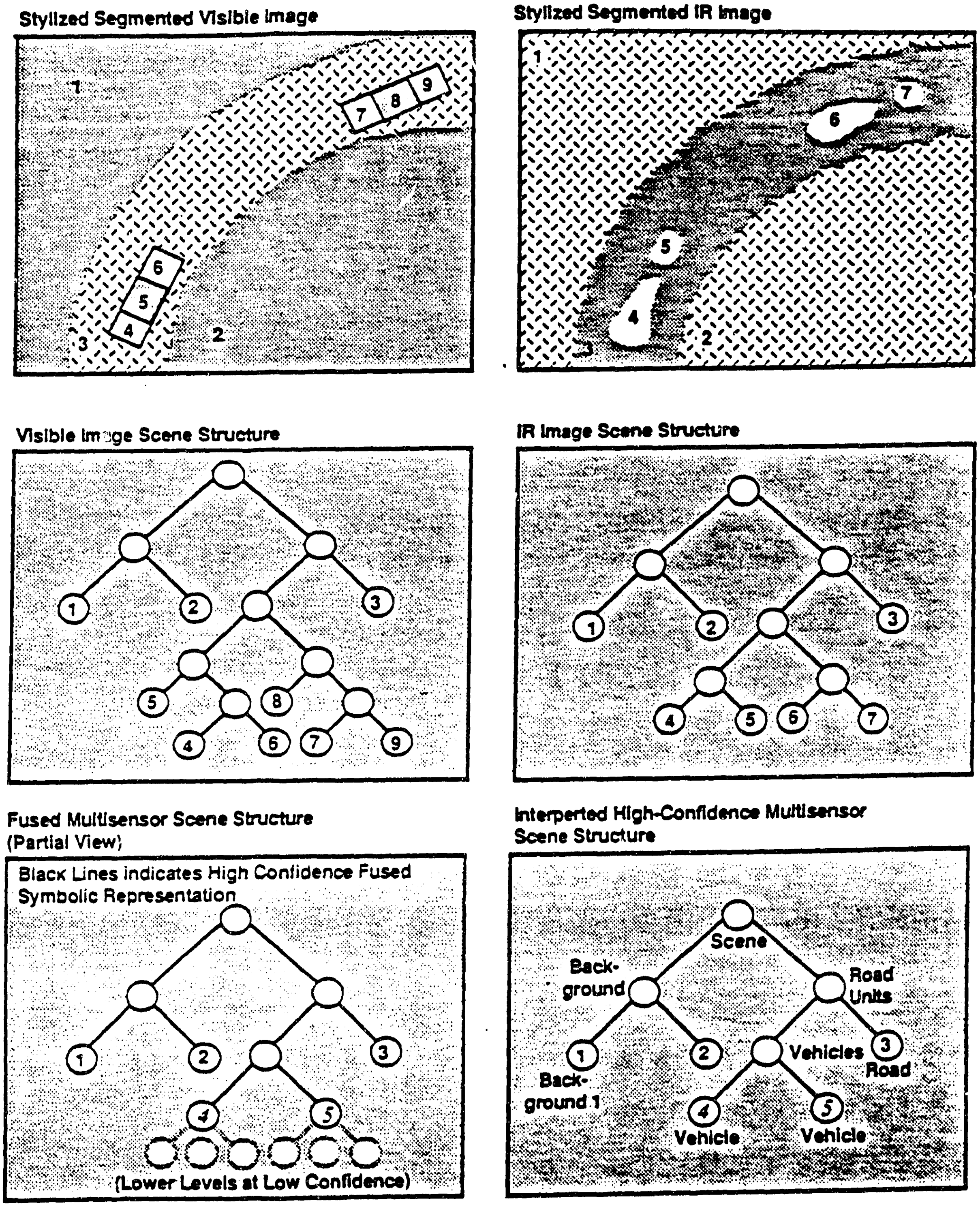


Figure 5. Illustration of how Hierarchical Scene Structures can aid multisensor information fusion. (a) & (b), stylized synthetic images of a convoy as taken from visual and IR cameras. (c) & (d), Hierarchical Scene Structures created from (a) and (b), respectively. (e), Multisensor-fused Hierarchical Scene Structure (MHSS). (f), interpreted structure.

The Hierarchical Scene Structure method can be modified to be used for fusing temporally-varying signals, including sonar, radar, and seismic data. This is vital in areas where a large amount of information from multiple sensors needs to be analyzed many times per second and per sensor. Neural networks have the potential to process this type of data and compare it with other information. This information can then be discriminated against other information to provide a viable recognized pattern.

Our current work focuses on extending our HSS method to representing temporally-varying signals, such as would be observed in sensor data readouts. We are also extending our cooperative/competitive method for creating initial HSS's to create a robust method for matching HSSs against existing models and for fusing HSSs to create an MHSS.

To perform this fusion, we first segment each data stream into "events," as shown in Figure 6 (a) & (b). Each event, along with its features, is represented as a node in temporally-evolving linked list, as shown in Figure 6 (c) & (d). Using a multi-layer, cooperative / competitive network similar to that described in [Maren et al., 1988, and Maren & Ali, 1988], we can create a temporally-evolving chain of structures, as shown in Figure 7.

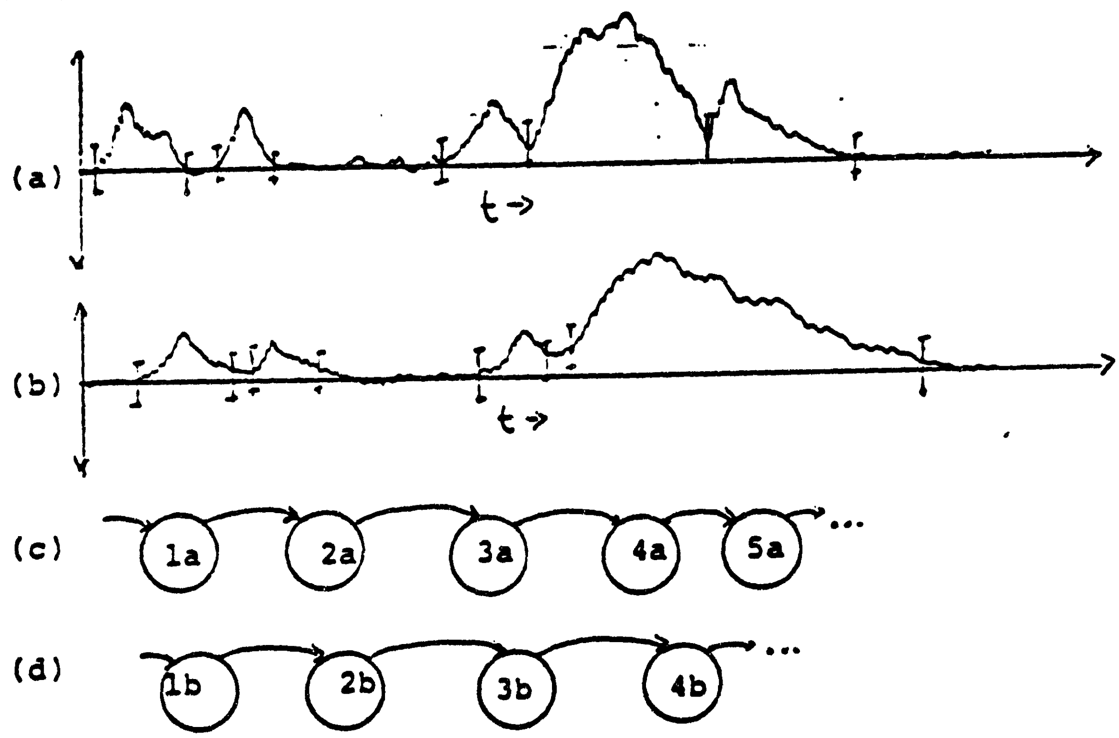


Figure 6. (a) & (b); Illustrations of sensor data from two sensors, sensor "a" and sensor "b." (c) & (d); Illustration of linked lists of segmented sensor events from the original data streams.

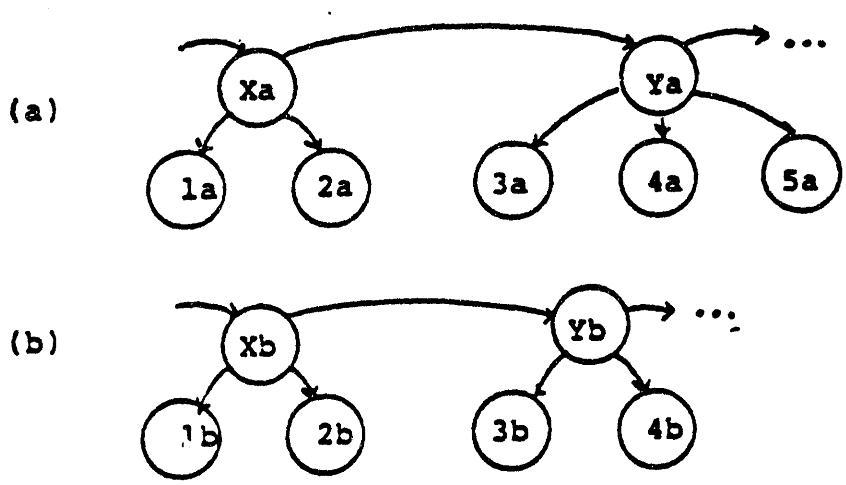


Figure 7. Illustrations of Hierarchical Data Structures created from the linked lists of sensor data events shown in Figure 6. Events are grouped together according to proximity and similarity, using a set of relational metrics. The grouping is carried out by a cooperative/competitive network.

Once HDSs have been created from the event lists from each sensor, they can be fused to create a Multisensor fused Hierarchical Data Structure (MHDS). This would result in both data compression and confidence evaluation of the sensor data events observed. The MHDS can be used to generate feedback that can help validate the performance of each of the contributing sensors. An MHDS is shown in Figure 8.

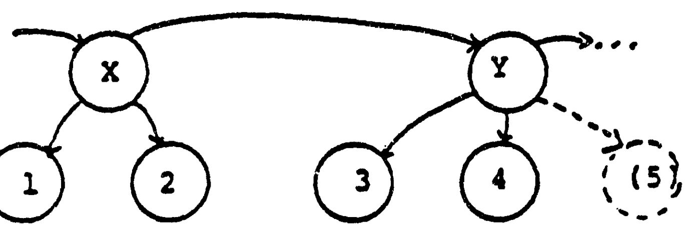


Figure 8. The two HDSs shown in Figure 7 are fused into a single MHDS. Nodes representing similar events are fused, resulting in data compression. Since node Y for both sensors (a) & (b) contains information about all subordinate nodes, fusion at Y overcomes the difficulty which would be experienced if efforts were made to fuse regions 4a, 5a, and 4b directly.

5.0 HOW CAN STRUCTURE-BASED MSIF BE USEFUL?

The benefits which can be achieved through high-level, structured fusion of multisource information include increased accuracy of object/feature recognition under both controlled and natural conditions, greater specificity in characterizing object/feature attributes, and improved functionality of autonomous and semi-autonomous systems. Previous work has pointed the way to the benefits which could be achieved, but has also shown how difficult the task of MSIF truly is. The technical approach offered here provides a robust framework for symbolic information integration and for making the fused information accessible and useful.

We are investigating the use of associative neural networks to perform interpretation of fused information. The goal of this work is to associate fused information with meaningful concepts, which can be symbolically represented as words. Our approach to this problem, using an associative neural network cortical model, is patterned after the brain and is used to guide these research efforts. The cooperative/competitive component of the system is a proven concept. Additional work continues on the organization of the association process. Current activity is involved with extending the systems'range of applicable input, including digital data representations and data structures.

Certain of today's VLSI integrated circuit technologies allows for interface with a microprocessor and eye pattern generator. These could be used to directly capture on-site or remote imaging sensor data for an MSIF/HSS processor. The possibility exists that incoming sensor data could be interpreted in real-time as it is received. Conceptually, distortion correction, digitization, reduction and magnification as well as image signal enhancement can be developed for this system in a relatively small and fieldable unit. The unit would maintain electronic files and be capable of byte transfer as well as high speed transfer modes. Neural network technology is becoming available in integrated circuits that could then interface into the system.

The MSIF/HSS/HDS is becoming a technology that can be adapted to use in many future applications.

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