Image Understanding Research For Automatic Target Recognition

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ABSTRACT

Automatic Target Recognition (ATR) is an extremely important capability for defense applications. Many aspects of Image Understanding (IU) research are traditionally used to solve ATR problems. In this paper, we discuss ATR applications and problems in developing real-world ATR systems, and present the status of technology for these systems. We identify several IU problems that need to be resolved in order to enhance the effectiveness of ATR-based weapon systems. Finally, we conclude that technological gains in developing robust ATR systems will also lead to significant advances in many other areas of applications of image understanding.

INTRODUCTION

Automatic Target Recognition (ATR) is the process of automatic target acquisition and classification. All the services need ATR capability [11] for a variety of missions and scenarios such as air-to-ground, ground-to-ground, surface-to-surface, air-to-air, etc. ATR systems that can work in multiscenarios do not exist yet. However, there exists a strong need for developing automatic target recognizing systems that can perform effectively in dynamic environmental conditions [1].

The generic ATR problem is to take information from one or more sensors, and if necessary, combine it with *a priori* information. A decision is then made about the type of targets present in the scene. The targets are usually prioritized by their tactical importance so that appropriate actions can be taken in a given situation once their presence has been inferred. Table 1 shows the variety of sensor types, weapon platform types, target types and the *a priori* information that is available for ATR applications. The atmospheric absorption of energy in the electromagnetic spectrum determines the utility and guides the development of visible, forward looking infrared (FLIR), laser radar, microwave/millimeter wave radar and acoustic sensors commonly used for ATR applications. Table 2 shows the principles of operation and performance characteristics of these sensors for target recognition.

The term ATR includes both autonomous and aided recognition (or cueing with a "person in the loop"). In cueing, the acquisition is done by the targeting system, but ultimately recognition is done by the person. Although many researchers would like to perform a wide variety of missions autonomously, the services will only automate critical operator functions reluctantly. There is a built-in bias toward the flexibility of the human operator (e.g., the Air Force relies on manned, strategic nuclear bombers despite excellent land and sea based strategic missiles). There is more willingness to remove the operator from the missions where survivability of humans is low. Soldiers may be moved further from the "action," but are not expected to relinquish control. Aided systems with a "person in the loop" will be employed before autonomous ones.

It has now been established that ATR is a multidisciplinary area that requires diverse technology and expertise in sensors, processing algorithms, architectures, implementation, and evaluation of software and hardware systems. The related computer vision and pattern recognition technology and systems have evolved from using the statistical pattern recognition approaches to model-based vision, to knowledge-based systems. Recently, adaptive and learning systems focused on parts of ATR problems are also being developed in laboratories.

Image understanding (IU) is synonymous with computer vision. One of the important goals of IU is to develop techniques

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Table 1. Variety of Sensors, Platforms, Targets and *a-Priori* Information Used in ATR Applications

Type of Sensors	Visible Infrared Laser Seismic Acoustic Millimeter Wave, Synthetic aperture radar (SAR), Inverse SAR Combinations of the above sensors
Type of Platforms	Ground vehicle Aircraft Missile Ship
Type of Targets	Mobile - Tanks - Helicopters - Ships at sea Fixed - Storage depots - Bridges - Ships in ports
***A-Priori* Information**	Tactics Digital Map Meterology Intelligence

In this paper, we first present typical ATR applications for various services in Section 2. This is followed by a discussion of technological problems in developing real-world ATR systems Section 3. Section 4 presents the current status of technology for ATR systems. In Section 5 we identify and discuss technical research areas related to ATR and image understanding. Finally, in section 6 we present the conclusions of this paper.

ATR APPLICATIONS

Table 3 shows several defense applications of ATR. The attack helicopter application for Army is probably the highest priority for ATR insertion. It is a good example of the functional capability desired. The mission is currently performed in the Army by the Apache helicopter with a crew of a pilot and weapons operator. The weapons operator, by viewing through an optical telescope, day TV, or thermal infrared imager, selects targets which are designated by a laser. Hellfire missiles fly

Table 2. Principle of Sensor Operation and Performance Characteristics

Sensors	Mode	Principle of operation	Performance characteristics
Visible	Passive	Visible light projected through a lens onto a solid state sensor array.	Very high resoultion image. Day operation only. Affected by environmental conditions. No foliage penetration. Atmospheric range is limited by visibility conditions.
Infrared (FLIR)	Passive	Thermal 2-D image using mechanical scanning or focal plane IR receptor array.	High angular resolution. Day/night operation. Affected by rain, fog and haze. Poor cloud and foliage penetration. Atmospheric range 10-15 Km.
Laser Radar	Active	Direct range measurement by scanning the scene with a coherent light source. Narrow beam-width allows high angular resoultion. Can produce range, reflectance and velocity data. Range measurement through time-of-flight or phase difference.	Moderately high resolution. Day/night operation and countermeasure resistence. Affected by rain, fog and haze. Poor foliage penetration. Atmospheric range ~5 Km.
Microwave/ Millineter wave (MMW)	Active	Direct range measurement by scanning. Can produce range, intensity and velocity data.	Moderate resolution. All weather - less sensitive to weather effects than laser sensor. Day/night operation. Large search area. Atmospheric range could be very large. Penetrates foliage at lower frequencies. Target recognition for SAR/ISAR and MMW.
Acoustic	Passive/ Active	Range and velocity measurement by transmitting a high-bandwidth pulse, chirp, or continuous sound.	Poor resolution. Attenuation depends on medium(air, water) and transmitter frequency. Useful range in air ~20m; in water - several hundred meters.

for automated 3-D scene interpretation. Key applications of IU are ATR, autonomous navigation, photointerpretation, cartography, automation for manufacturing and quality control.

Table 3. Typical ATR Applications

ARMY	NAVY	AIR FORCE
Fire-and-forget anti-tank missiles for infantry	Undersea vessels using acoustics	Pilot assistance
Smart minefields	Detection and recognition of surface ships	Detection and recognition of fixed, high-value targets
Targeting for artillery	Anti-ship missiles	Detection and recognition of mobile targets like advancing tanks
Air defense	Air-to-air fighter identification	Detection and recognition of hidden targets like SCUDs
Tank commander and gunner assistance	Infrared Search and Track (IRST)	Air-to-air fighter identification
Perimeter surveillance		
Attack helicopter missions		

to the laser spot on the target. The time taken by the operator searching for targets makes this platform vulnerable to enemy anti-aircraft fire. To shorten this time, in the new Commanche Helicopter, the operator will be assisted by an ATR process that possesses the sensor information and directs the operator to suspected targets.

The Navy's largest effort on detection and recognition focuses on undersea vessels using acoustics. This application is highly classified and does not overlap significantly with surface applications. Finding surface ships is done primarily with radar. There is a need for anti-ship missiles to autonomously attack the most valuable (dangerous) ships in enemy battle groups. This requires ATR capability. Both the Navy and the Air Force share the need for air-to-air fighter identification.

The Air Force is the primary service for conducting air strikes into enemy-held territories. This covers close air support, attacks on second echelon forces tens of kilometers from the battle, and deeper resupply, power plant, rail centers, or storage depots. The detection of mobile targets like tanks and that of hidden targets like SCUDs are the more challenging ATR applications. The fixed targets allow for sufficient time to prepare references and attack profiles that make the ATR, task easier.

The main distinction between tactical and strategic targets is in the significance of the targets. In the ATR world, it is generally easier to automate the functions against the strategic targets than tactical ones because more resources can be devoted to the problem. Also, in tactical situations, the background is continuously changing because targets are generally mobile. The underlying processing technologies for tactical and strategic situations are quite similar.

It is to be noted that the effectiveness of autonomous, smart weapons guided by multi-sensors that we have witnessed recently during Desert Storm was almost entirely against fixed targets. This allowed significant mission preplanning. To achieve comparable results against mobile targets will require a major infusion of ATR technology.

Because of the wide variety of missions, sensors, and functions which an ATR system may be required to deal with, there is no single solution to the algorithms or hardware tasks. For each application, the information available or attainable must be uniquely matched with the appropriate processing required for the functional needs of the mission.

PROBLEMS IN DEVELOPING REAL-WORLD ATR SYSTEMS

The nature of the ATR problem is characterized by non-repeatability of target signatures, competing cluttered objects, obscured targets, low contrast (for some sensors), long range (low resolution), conflicting evidence, natural variability, presence of camouflage, concealment and deception, and a wide variety of outdoor scenarios (different geographic areas, battlefield conditions and weather), etc. [1,23]. As an example, Figure 1 shows multimodal and low-contrast FLIR (Forward Looking InfraRed) images. Some of the problems associated with developing ATR systems are:

Robust Algorithms

The key scientific problem is the absence of robust image understanding algorithms, for detecting, classifying, recognizing and identifying 3-D objects from 2-D, 2-1/2-D and 3-D images, that can work in multiscenarios with varying environmental conditions. Current image understanding algorithms for image segmentation, recognition and multisensor integration do not provide the necessary consistency, reliability and predictability of results. For example, current algorithms result in high false alarm rates in images with high clutter and poor recognition performance in images without well-defined target signatures. They make very little use of *a priori* information related to and present in the image, and generally make little use of meta-knowledge control.

Validation and Performance

In the current ATR systems, there is an absence of validation of data and models. Although we can measure some performance, such as probability of detection, probability of false alarm and probability of recognition, we lack metrics to measure the input, i.e., useful techniques to characterize the input data (e.g., image complexity) are not available. Also, there are problems associated with real-time performance evaluation. Current experience in the ATR field is only with limited multisensor databases which are not very representative of scenario variability. Thus, there exists a need for suitable multiscenario databases.

Lack of Specific Mission Requirements

Because the users of this technology do not have a clear idea of what capability is achievable, there is a reluctance to establish firm requirements. Instead, all the services have listed ATR as a desired capability for a variety of missions. A panel under the DoD Working Group on ATR Technology [12] has listed these mission needs. However, the recent major shift in the perceived U.S. threat is likely to modify this.

Software/Hardware

There are problems associated with specialized or general-purpose efficient processor architectures with hardware/software programmability and managing both numeric and symbolic computation. General purpose architectures are hard to optimize with respect to specialized processing and special-purpose architectures have problems with flexibility and programmability. Also, there are no standard modules (e.g., image segmentation, feature extraction, recognition) in hardware or software, to allow economy of scale to reduce costs.

Computational Power

Since the mission is not specifically defined, there is no simple answer to required computational throughput. It is clearly a function of the bandwidth of the incoming data, the functions to be performed, and the complexity of those functions. In most cases, the processing will be expanded to the capability of the available hardware. Today, this means that algorithms can be developed using billions of operations per second for applications requiring no more than a few small cards. We need at least giga to tera bytes of storage and giga to tera floating-point operations per second for practical ATR systems. Even a bee has more than giga bytes of storage and performs about tera operations per second [8].

Man-Machine Interfaces

Current target cueing technology can provide reasonable help in the field. However, the important research issues related with cueing are reliable target acquisition and man-machine interfaces for presenting the information in a clutter free manner (in video, audio or contact mode) to the operator/pilot. The interface concepts are just beginning to emerge about how to best use the operator and ATR together. What information is required and how and when to pass it, are some of the unresolved issues for most applications. Virtual reality and visualization technology can be used to understand man-machine interface issues and approaches, and carry out performance evaluation of ATR algorithms.

Technology Transfer

As a result of the proprietary nature of algorithms and systems, sharing of algorithms, software, hardware and data is difficult. Recent attempts by the government to acquire software developed under the government contracts and its distribution to the ATR community is helpful. Further, the involvement of the university community and the availability of unclassified data will result in more cooperation and productive partnership between universities and industries. The newly started ARPA University Research Initiative into the Theory and Strategies for Automatic Target Detection/Recognition is a step in this direction [9]. Image Understanding Environment (IUE) [19] and Image Understanding Architecture (IUA) [24] will also contribute to the technology transfer process. IUE will provide uniform environment for software development and evaluation for various applications of IU.

Fig. 1A. A Multi-Modal FLIR Image

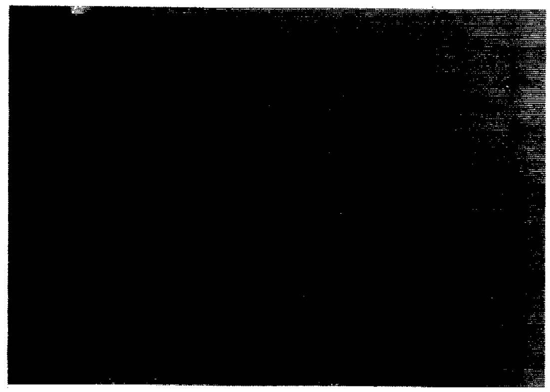

Fig. 1B. A Low-Contrast FLIR Image

IUA is a tightly coupled, heterogeneous parallel processor to support real-time knowledge-based vision application. It has a fine-grained Single Instruction Multiple Data (SIMD)/Multi-associative array for low-level vision, a medium-grained Single Program Multiple Data (SPMD) array for intermediate-level vision and a coarse-grained Multiple Instruction Multiple Data (MIMD) array for high-level, knowledge-based processing. Some of the ATR algorithms should be tried on IUA once it becomes available. IU algorithms for ATR have many other applications for both defense and civilian purposes.

STATUS OF TECHNOLOGY FOR ATR SYSTEMS

Significant progress has been made during the last ten years from ad-hoc techniques like looking for hot spots in infrared images by thresholding on contrast measures to more scientific understanding of sensors, algorithms, architectures, processors, systems and associated technology for software/hardware implementation [6]. Newer microelectronics technology has allowed implementation of more complex algorithms.

During this time, the need for better databases used in training and testing ATR systems has been realized. Although more and better data will always be desired, several data sets have been established with ATR development in mind. In general, they have been characterized better than previous data sets and often have machine readable ground truth or image truth with them, rather than just hand-scribbled log books.

The processor technology has been revolutionary. In 1980 an algorithm often took 30 minutes or more to run on a general purpose computer such as a VAX 11/750. To get the times down to a few seconds, in order to process a large number of images, dedicated processors were required for which algorithms could not be changed without modifying the hardware, a task often requiring several months. Today, commercial signal processing hardware (such as Datacube hardware, signal processing chips like TMS 320C40 from Texas Instruments Inc., etc.) exists to perform many of the component modules needed in ATR functions. This hardware is quite valuable in an R&D environment.

Simple algorithms to achieve real-time performance have been implemented in hardware and several such systems exist [11]. Some of these systems have also been field tested. These systems are based purely on statistical pattern recognition algorithms. They employ limited multiframe processing analysis and possess no countermeasure capability. With inadequate training data, these algorithms alone could never hope to achieve the robustness required in many military applications. Only for limited low clutter and high contrast FLIR imagery, the detection and classification performance has been satisfactory.

At present, in laboratory prototypes (using Datacube hardware or special purpose chips) or in Simulation (on serial/parallel processing machines), ATR systems employing more complex algorithms and cross-sensor features including some model-based ATR algorithms are being developed. For example, Multifunction Target Acquisition Processor (MTAP) [16] has more than 80 modules based on DataCube and Motorola cards and provides the user with immediate access to algorithms, parameters, and results. These systems use single (e.g., FLIR imagery for the MTAP system [16]) or multisensors (i.e., FLIR, MMW, LADAR, SAR, etc.) but make limited use of models, *a priori* information, countermeasure resistance, uncertainty propagation, and scene analysis techniques. They have been tested on very small databases. Only for unobstructed medium contrast FLIR imagery, the recognition performance has been from marginal to satisfactory. Truly model-based multisensor ATR systems do not yet exist in real-time hardware systems.

There is now a larger set of "Tools" in the algorithm developers "toolbox." They include knowledge-based tools, model-based tools, neural-nets, and genetic algorithm techniques. However, no one of these techniques, alone, is likely to be the solution to all ATR problems, but by applying the most useful techniques to each piece of the problem, progress is accelerating. Table 4 summarizes the key algorithmic issues and state-of-the-art for automatic target recognition.

Table 4. Key Algorithmic Issues and State-of-the-Art for Automatic Target Detection and Recognition

Key Algorithmic Issues	State-of-the-Art in Automatic Target Detection and Recognition
Segmentation	ATD/R success depends on segmentation. For example, current techniques attempt to extract blob-like shapes in FLIR images. However, because of intensity gradient across targets (partly hot, partly cold), they are not extracted as a single blob. This causes distortion of shape features (e.g. contour) and results in high false alarm rates, particularly in cluttered scenes.
Occlusion	Contours of targets (for various aspects) are used for structural matching. These contours are quite sensitive to noise and partial occlusion, hence matching techniques are not robust.
Complex Terrain	Target detection techniques use very limited target and clutter models, resulting in unacceptable ATD/R performance in complex terrain.
Detection & Recognition based on multiple frames	Use of single-frame approaches for detection and recognition are not sufficiently robust, even for medium contrast imagery and moderately complex scenes.
Indexing	Generally exhaustive; hash coding has limited success in real-world data.
Multi-sensor integration	Ad-hoc techniques are commonly used for sensor integration, such as pixel-level, feature-level, and decision-level fusion.
Counter measures	Very limited capabilities.
Learning for Model Acquisition and Background characterization	For simple backgrounds, statistical/fractal models can be obtained. The assumptions made in Markov Random Field (MRF) models are not realistic.

CHALLENGING IMAGE UNDERSTANDING PROBLEMS

As discussed earlier, ATR is a system that involves sensors, algorithms and processors. The area where image understanding can significantly contribute is in algorithm development. New, improved, robust algorithms will help to increase the effectiveness and usage of ATR systems. They will provide a better understanding of complex interaction between input data, models and output results. In the following we relate ATR problems to image understanding and identify potentially new research areas in image understanding that will help to solve the ATR problems.

Characterization of Input to an ATR System

An ATR system may be viewed as an image processing/computer vision system that consists of a variety of multisensors and multisource data. It is desired to characterize the input to an ATR system so that we can relate the inputs to the outputs of the system. This relationship is required for understanding the behavior of the system under a wide variety of inputs. This analytic or parametric relationship in turn also helps to improve prediction capability, an important feature of a scientific field, and essential for practical uses of the system.

We know a number of measures (such as probabilities of detection, false alarm, confusion matrix, etc.) that we can use to evaluate the output of the system. However, we do not know precisely how to characterize the input (e.g., image complexity). A number of simple information measures such

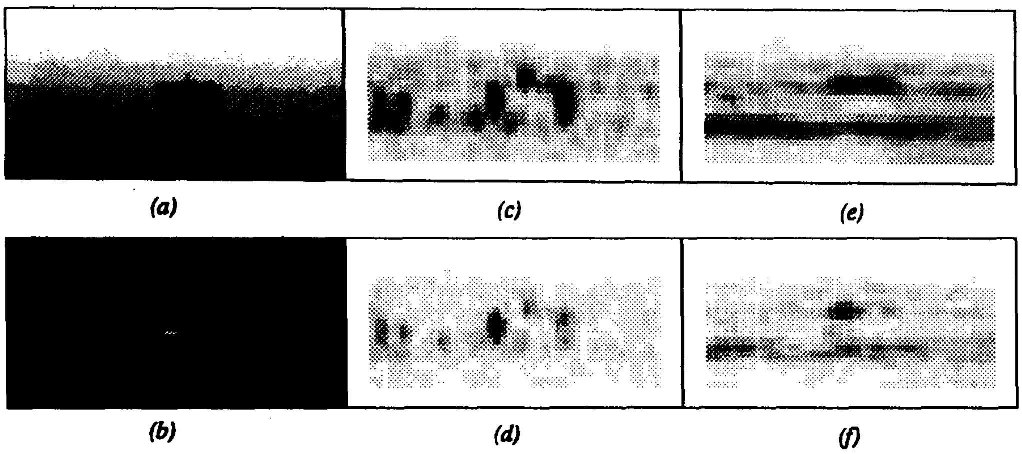

Fig. 2. Use of Multi-Sensor Data for Target Detection. 2A. Original Laser Range (LADAR) Image; 2B. FLIR Image; 2C. Gabor Magnitude for the Laser Image at Orientation Zero Degrees; 2D. Coincident Gabor Magnitude Response from LADAR and FLIR Images at Orientation Zero Degrees; 2E. Gabor Magnitude for Ladar Image at 90 Degree Orientation; 2F. Coincident Gabor Magnitude Response from LADAR and FLIR Images at 90 Degree Orientation. Note the Distinct Peak Response in 2D and 2F in Spite of the High Noise and Poor Object Boundary Coincidence on the Target

as edge points, entropy, uniformity, and structural measures have been proposed in the past. However, they are of limited value in characterizing the input objects and clutter. We need better measures that are realistic and may provide insight into the behavior. We would like to have some fundamental results (like in Information Theory) that set the bounds on the performance for recognition that is based on the information content in the sensor and other relevant data.

Consolidated Recognition and Motion Analysis

In a typical ATR system, tracking is generally a component of the system. Tracking is normally done by using a multimode tracker consisting of some combinations of 2-D feature matching, centroid matching and correlation matching in association with Kalman filtering. In the past, the 3-D information available in a sequence of images has not been used to improve tracking within an ATR system. Further, in ATR systems and image understanding, motion analysis has not been used in close cooperation with recognition to improve the recognition rates [10,15]. Also, very little work has been done where recognition helps to improve motion analysis. An example of motion analysis aiding recognition is that of the information about the direction of vehicle motion constraining the viewpoint/aspect of the target. Similarly, recognition information will help in the determination of mobile or stationary targets which in turn will reduce the false alarm rate for motion analysis, thus helping to track targets under high clutter and low contrast situations.

The idea is to consolidate recognition and motion analysis in the following ways: (a) Use 3-D depth information to improve target tracking through occlusion and high clutter situations which in turn will improve recognition performance [2]; (b) Integrate tracking and recognition functionalities, where one improves the performance of the other. As an example, in the long range detection of aircraft signatures, IR signature of an incoming threat target is detected using a highly stabilized, high sensitivity IR sensor and by separating true targets from the background. Such a sensor is called the IRST (InfraRed Search and Track) [13]. Using the IRST sensor, target identity and range is passively estimated using known motion of the sensor and assumed motion of detected incoming targets. The idea is to use something like IRST for ground or surface targets.

(a) and (b) as described in the above can be developed independently or in conjunction with each other.

Also integrated recognition over multiple frames can be performed to improve performance of an ATR system in cluttered situations.

Model-based ATR

Model-based ATR is an extremely important research area and requires much advancement. In the IU/computer vision field, mostly visible and some laser and limited SAR data has been used [21]. We need to develop expertise in other sensors (such as FLIR, SAR, MMW, etc.) which are so vital to the development of practical systems [25]. Further, the IU community has mainly dealt with geometric models of objects and limited (visible, SAR) sensor models. Many things are desired here.

Model-based ATR involves developing not only the geometric models of the targets, but also the models for sensors, clutter, background, heat flow, atmospheric physics and countermeasures.

A capability to generate and predict in real-time the signatures of targets under varying condition (e.g., Forward Looking Infrared sensor) will be extremely valuable as are the needs for clutter and background models (based on texture or spectral analysis) commonly encountered in a specific ATR application.

Accurate and efficient development of sensor models (e.g., thermal, SAR waveform, multispectral, laser, etc.) and target models with suitable representations, and their use in model-based recognition and tracking, will be of importance in enhancing the recognition performance and reducing false alarms. An example of a new local representation (vs. global representation of Fourier transform), called Gabor wavelets [7] for multi-sensor based target detection is given in Figure 2.

It will also be desired to quantify the effect of sensor improvement with the performance of the system (not done heretofore) and validate various models used in the recognition process. Developing models for algorithm behaviors (characterized by analytical or parametric curves) relating input data/scene properties to algorithm behavior will be valuable. Also important are approximate model matching techniques, for the recognition of partially occluded targets in a dynamic environment, which may be suited for explicit control, and fast, parallel implementation.

Robust Algorithms

"Robustness" of an ATR system is the measure of insensitivity of performance, as measured by recognition and false alarm rates, to the deviations in assumed input conditions to the system. One way to characterize "robustness" of the algorithms could be to relate the input information to the performance of the algorithms. A measure of "robustness" could be the recognition performance and the number of false alarms for the same set of targets, but under different environmental conditions. The terms "robustness" and "multiscenario" are related. "Multiscenario" is implying "generality" of algorithms to work under varying environmental conditions in the outdoor scenario. "Robustness" as defined above and needed for ATR tasks is distinct from what it is commonly perceived, and misused/overused term in the IU community.

Robust algorithms for segmentation and 3-D object recognition are desired. Since a target may give rise to a limitless variety of images (varying viewpoint and environmental conditions), it is important to use all the available knowledge and sensor information to accomplish the system goals.

Adaptive Algorithms

Adaptive algorithms for segmentation, feature extraction and recognition strategies that can learn (parameters, concepts, etc.) and adapt to the varying environmental conditions will have one of the greatest impacts on ATR performance and its applications in a wide variety of practical situations [4,18,20]. The most important reason for this is that no matter how sophisticated an algorithm may be, it will always have some imagery or conditions that will cause it to breakdown unless it has inherent adaptive and learning capability. "Adaptiveness" ensures "robustness" as defined in the above. "Adaptive algorithms" are indeed "robust algorithms." However, adaptive algorithms may also possess self-calibration and learning capabilities which are not fundamental requirements for robust algorithms. Techniques for rapidly training these adaptive/learning subsystems are also desired. Learning can also be useful for application specific expert systems for knowledge acquisition [17].

Architectures for Integration of Auxiliary Information and Multisensors

The flexible open system architecture must be developed that will allow integration of knowledge databases for sensors, targets, platforms, *a priori* information and algorithms for target detection and recognition. Current multisensor integration technology is based on the competitive, cooperative and complementary behaviors of sensors and uses pixel, feature, and decision level fusion of information for ATR. This technology must be augmented with a priori information to provide improvement in target detection and classification performance. Use of auxiliary information like maps, navigational sensors, metrological data, altimeter, etc., into the recognition and tracking process will be extremely valuable in enhancing recognition and reducing false alarms.

(a) Fusion—It implies the integration of mission-based, model-based integration of sensors together with relevant data and information. Multisource information integration may include intelligence, mission planning, geography, doctrine, in-flight updates, previous sightings, meterology, and models for target, clutter, countermeasures, sensors, etc. Integration process should allow for mission specifics and evidence-based reasoning so as to follow suitable recognition strategy based on available resources and their optimal use. All this will ensure the effectiveness of performance.

(b) Knowledge databases—Good target recognition will not be achieved unless one updates knowledge databases dynamically so as to adapt to the changing situations and mission needs. Currently, necessary software technology base is far behind to do automatic knowledge acquisition and refinement of existing knowledge [17]. This makes the use of architecture difficult.

Recognition and Guidance of Sensors

There are many mission scenarios for ATR systems where recognition and guidance of available sensors are closely related for extracting desired information or verification of a hypothesis about a particular target. In the IU community, active vision and task-based vision paradigms have been popular for several years [22]. Active vision paradigm requires a dynamically reconfigurable vision system and a set of intelligent control strategies to acquire visual data using this system. For this technology to have an impact on the ATR problem, we need to apply this technology to the outdoor real-world scenarios where the problem complexity is significantly higher than in the indoor scenarios [5].

Parallel Algorithms and VLSI

Inherently parallel algorithms (not a parallel version of a serial algorithm) and mechanisms for mapping algorithms to specialized architectures need to be developed. Real-time digital/analog VLSI implementation of algorithms and subsystems/modules (e.g., moment chip, segmentation chip, etc.) useful in various applications need to be developed [3,14]. A lot of it can be done in a university/industry collaboration by developing and expanding working relationships between industries and universities with support from the government.

Real-time Performance Evaluation

A framework for building vision systems must be developed so that real-time evaluation and performance characterization of algorithms can be done in laboratory prototypes or in actual field tests. This framework needs to be common among various sites so pieces that are useful from various researchers can be integrated together. The availability of some state-of-the-art multisensor, registered database of images and associated ground truth to IU researchers will be very valuable. Standard data sets for various applications can help focus the research efforts, allow comparisons and expand the expertise of the IU community to ATR problems.

Man-Machine Interfaces

Suitable interfaces (with audio, video and tactile) need to be developed to apply the image understanding and human factors technology to the "person in the loop" situations.

CONCLUSIONS

To reduce the workloads of pilots and tank commanders and be able to be effective in hostile situations requires the development of automatic target recognition systems that can perform under dynamic environmental conditions. ATR systems will also be of great practical significance in many other defense applications. We hope that the solution of image understanding problems as discussed in this paper will lead to further discussions of image understanding research for ATR application. All this will result in scientific advancements in the image understanding field and more efficient and robust ATR systems in the future. The technology developed will also be applicable to other areas of image understanding applications such as navigation, photointerpretation and robot vision.

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