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Report Title

Tracking Using Peer-to-Peer Smart Infrared Cameras

ABSTRACT

This project has two complementary goals: to develop new methods for video tracking using multiple, physically distributed cameras without relying on centralized servers; and to develop new algorithms for tracking using infrared images. We must develop target models for infrared that are robust to changes in target orientation, illumination, and environmental conditions. In general, the best results are obtained by fusing data: fusion of multiple channels, such as visible and infrared; and fusion of estimates from the physically distributed nodes in the system. We are particularly interested in physically separated cameras---practical systems will not always have a visible camera and an infrared camera paired at every node.

We must develop peer-to-peer protocols that allow reliable operation of a distributed set of cameras and processors. Protocols are at the heart of distributed computing systems. These protocols must operate in real time to avoid losing tracking data.

List of papers submitted or published that acknowledge ARO support during this reporting period. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

• Senem Velipasalar and Wayne H. Wolf, "Frame-level temporal calibration of video sequences from unsynchronized cameras," Machine Vision and Applications Journal, DOI 10.1007/s00138-008-0122-6, January 24, 2008.

• Senem Veliapasalar, Jason Schlessman, Cheng-Yao Chen, Wayne H. Wolf, and Jaswinder P. Singh, "A scalable clustered camera system for multiple object tracking," EURASIP Journal on Image and Video Processing, v. 2008, article ID 542808, 2008.

• Senem Velipasalar and Wayne Wolf, "Lessons from a distributed peer-to-peer smart tracker," Elektrotechnik and Informationstechnik, 2008, 125/10, 1-7.

Number of Papers published in peer-reviewed journals: 3.00

(b) Papers published in non-peer-reviewed journals or in conference proceedings (N/A for none)

Number of Papers published in non peer-reviewed journals:

(c) Presentations

0.00

Number of Presentations: 0.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

• Jason Schlessman, Ikdong Kim, Jaechang Shim, Yun Cheol Baek, and Wayne Wolf, "Low power, low cost wireless camera sensor nodes for human detection," in Proceedings, Sensys 06, ACM, 2006.

Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Peer-Reviewed Conference Proceeding publications (other than abstracts):

1

0

• S. Velipasalar, J. Schlessman, C. –Y. Chen, W. Wolf, J. P. Singh, "SCCS: A Scalable Clustered Camera System for Multiple Object Tracking Communicating via Message Passing Interface "IEEE International Conference on Multimedia & Expo, July 2006.

• S. Velipasalar, C. H. Lin, J. Schlessman, W. Wolf, "Design and verification of communication protocols for peer-to-peer multimedia systems "IEEE International Conference on Multimedia & Expo, July 2006.

• Cheng-Yao Chen and Wayne Wolf, "Background modeling and object tracking using multi-spectral sen¬sors," in Proceedings, ACM Workshop on Video Surveillance and Sensor Networks, ACM, 2006.

• Jason Schlessman, Mark Lodato, Burak Ozer, and Wayne Wolf, "Heterogeneous MPSoC architectures for embedded computer vision," in 2007 IEEE International Conference on Multimedia and Expo, IEEE, 2007, pp. 1870-1873.

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

(d) Manuscripts

Number of Inventions:

Graduate Students				
NAME	PERCENT SUPPORTED			
Cheng-Yao Chen	0.50			
Senem Veliapasalar	0.50			
Jason Schlessman	0.25			
Tai-Ming Lin	1.00			
Chung-Ching Lin	1.00			
FTE Equivalent:	3.25			
Total Number:	5			

Names of Post Doctorates

NAME	PERCENT_SUPPORTED	
FTE Equivalent: Total Number:		

Names of Faculty Supported				
NAME	PERCENT_SUPPORTED	National Academy Member		
Wayne Wolf	0.00	No		
FTE Equivalent:	0.00			
Total Number:	1			

Names of Under Graduate students supported

NAME

PERCENT SUPPORTED

FTE Equivalent:

Total Number:

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period The number of undergraduates funded by this agreement who graduated during this period: 0.00 The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:..... 0.00 The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:..... 0.00 Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale): 0.00 Number of graduating undergraduates funded by a DoD funded Center of Excellence grant for Education, Research and Engineering: 0.00 The number of undergraduates funded by your agreement who graduated during this period and intend to work for the Department of Defense 0.00 The number of undergraduates funded by your agreement who graduated during this period and will receive scholarships or fellowships for further studies in science, mathematics, engineering or technology fields: 0.00

NAME

Total Number:

Names of personnel receiving PHDs

<u>NAME</u> Senem Veliapasalar Cheng-Yao Chen **Total Number:**

2

	Names of other research staff
NAME	PERCENT_SUPPORTED
FTE Equivalent: Total Number:	

Sub Contractors (DD882)

Inventions (DD882)

Tracking Using Peer-to-Peer Smart Infrared Cameras

ARO Contract W911NF-05-1-0480 Final report: October 1, 2005 --- September 30, 2008 Wayne Wolf, School of ECE, Georgia Institute of Technology

Objective

This project has two complementary goals: to develop new methods for video tracking using multiple, physically distributed cameras without relying on centralized servers; and to develop new algorithms for tracking using infrared images.

Approach

Distributed smart cameras: We must devise peer-to-peer tracking algorithms that exchange information directly between cameras and processors. Central servers simplify programming but make the system less reliable. At the heart of a distributed smart camera is a protocol that allows the cameras to exchange information reliably.

Infrared tracking models: We must develop new target models that allow the tracker to identify targets and to distinguish the identity of targets in a multi-target scene. These models must be robust in the sense that they are relatively invariant to changes in the orientation of the target relative to the cameras. They must also be computationally inexpensive. We are interested in fusing infrared and visible images from physically separated cameras.

Scientific Barriers

Distributed tracking using infrared cameras requires advances in two distinct areas: distributed computing and image processing/computer vision.

We must develop target models for infrared that are robust to changes in target orientation, illumination, and environmental conditions. In general, the best results are obtained by fusing data: fusion of multiple channels, such as visible and infrared; and fusion of estimates from the physically distributed nodes in the system. We are particularly interested in physically separated cameras---practical systems will not always have a visible camera and an infrared camera paired at every node.

We must develop peer-to-peer protocols that allow reliable operation of a distributed set of cameras and processors. Protocols are at the heart of distributed computing systems. These protocols must operate in real time to avoid losing tracking data.

Significance

Infrared tracking is an important modality in harsh environments. The combination of infrared and visible imagery is especially powerful. Infrared imaging encompasses a broad range of infrared frequencies that have different characteristics, but infrared imagers can see through some kinds of haze and can identify people and vehicles in poor lighting conditions. We believe that physically distributed visible and infrared cameras are particularly important to Army applications. Since visible cameras are cheaper, they will be more plentiful. Infrared cameras may not always be co-located with visible cameras. Even if they are co-located, it is difficult to accurately align the two cameras since they use different optics. We need to develop algorithms that can tolerate infrared/visible misalignment.

Distributed smart cameras offer both improved tracking performance and fault tolerance. When a target is tracked by a single camera, the target may be occluded by an obstacle, forcing the system to lose track of the target. When a scene is covered by several physically separated cameras, the subject is much more likely to be visible to at least one camera in the scene. Using distributed computers to process the imagery makes the system fault tolerant---the network can continue to function when individual nodes are lost. Distributed tracking, when properly designed, also provides lower latency, meaning that targets are identified and tracked more quickly. We argue that traditional multi-camera, server-based systems are inherently undeployable in the field. Server-based architectures require raw video to be sent to the central server. Even if wireless networks allow the video to be transferred, the network requires a large amount of power to send the large volumes of data. This large data transfer is also vulnerable to interception, jamming, and other security problems.

Accomplishments

We have concentrated on new results in infrared/visible image fusion and analysis. We have been greatly helped in these results thanks to the equipment from our DURIP award.

We have achieved several significant goals over the past year relating to both infrared image analysis and peer-to-peer architectures:

- We developed new object models for multi-spectral imaging, including infrared and visible light cameras. These models do not require cameras to be optically aligned.
- We developed a true peer-to-peer, fault-tolerant tracking system.
- We developed new methods for multi-camera calibration and gesture recognition from multi-spectral camera setups, including infrared and visible cameras.

Result: We developed new object models for multi-spectral imaging. These models are useful in both single-camera and multi-camera systems. We use both infrared and visible imagery to separate background from foreground. These models use confidence factors to determine the relative importance of infrared and visible data in each region of the image. For instance, if both channels agree on whether a given region is foreground or background, that assessment is given higher confidence.



Visible only

New IR/visible model

Figure 1: A comparison of target splitting using visible only vs. our combined infrared/visible target model.

We also use an object model to help distinguish objects and resolve occlusion problems. In the visible channel, we estimate the direction of illumination from shadows to help determine the true extent of an object. In the infrared channel, we assume that the target's heat signature does not change significantly during the video sequence. We use confidence measures to combine the information from the channels. Figure 1 shows results of this model, which results in improved separation of targets.

Impact: These new models provide more accurate tracking of human subjects from single and multiple node camera systems.

Result: To provide fault-tolerant distributed camera networks, we developed SCCS, a peer-to-peer tracking system. This system uses a protocol to communicate between camera nodes. The system does not rely on a central server. It keeps redundant data at the various nodes so that cameras can estimate the position of objects even when a node fails. The nodes do not trade raw video data---they only communicate object models consisting of appearance and position information. When an object is occluded from the view of one camera, that node communicates with other nodes to determine the position of the occluded object. We have demonstrated this system on a three-node setup. Each node has a visible camera and its own processor, with the nodes connected by a standard network.

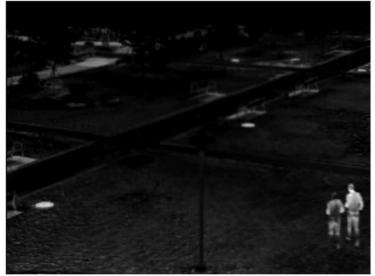
To support this peer-to-peer architecture, we developed a novel algorithm for synchronizing cameras using image processing. The cameras must be synchronized so that equivalent frames are compared. Our algorithm uses tracking-based search to find the best match between video frames.

Impact: We believe that this is the first fault-tolerant tracking system. The cameras share no central computation or communication resource. Information is stored redundantly around the network so that nodes can continue to operate when other nodes drop out.

Result: We created a new set of visible/infrared benchmark videos for tracking. These benchmarks were made with two pods of cameras that were located about 50 feet apart. The visible sequences were shot in high-definition (1080P) video. The infrared sequences were shot with Flir thermal cameras.

Impact: These benchmarks have allowed us to study more closely the relationship between visible and infrared images. We hope to release these benchmarks on the World Wide Web.

Result: We generalized our multi-modal data fusion model to handle non-co-located cameras.



Infrared input image



Visible input image



Transformed infrared image

Figure 1: Transforming the coordinate space of an infrared image.



Figure 2: Tracking results.

Visible and infrared cameras may not always come in pairs---we may have infrared cameras placed separately from the visible cameras. Our previous visible/infrared fusion method required that the cameras be co-located so that pixels could be matched in the two images. We developed geometric transformation algorithms to translate the infrared image into the visible camera coordinate system. These transformations require 3-D information to be able to adjust for the height of the target. Figure 1 shows the original visible and infrared frames, which were taken from cameras that were about 50 feet apart. The bottom infrared image was transformed into the visible image's coordinate system: the ground plane and the target required separate transformations.

We then generalized our multi-modal data fusion algorithm to handle the transformed infrared image. The results were somewhat disappointing---performance did not improve when the transformed image was fused with the visible image, when compared to the visible image only. This is because the pixels must be compared to identify regions in the image and it is difficult to transform coordinate spaces accurately enough to properly register the two sets of pixels. This is particularly true since the target's transformations change as it moves.

Based on this experience, we plan to concentrate on object-level fusion algorithms over the next reporting period. These algorithms will generate regions from the individual images, then fuse them at the object level using approximate geometric relationships between the two cameras.

Impact: First demonstration that we know of fusing data from widely separated visible/infrared cameras. We will use this experience to develop new object-based visible/infrared fusion methods.

Result: We measured the communication performance of MPI. MPI is a middleware system for grid computing, designed originally to support large scientific computations. We used it as the communication layer for SCCS. MPI offered sufficient performance for a three-node system, but we wanted to learn whether MPI would be fast enough for a large network of cameras.

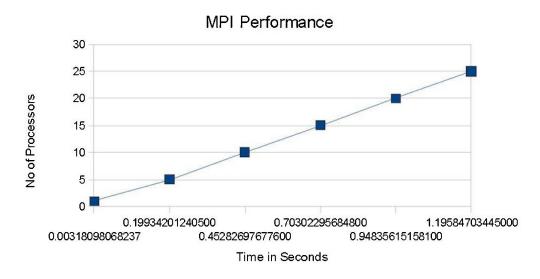


Figure 3: Communication speed of MPI as a function of number of processing nodes.

Figure 3 shows the results of our performance measurement. Communication time goes past one second for a network of 25 nodes. Since camera networks of this size are quite possible in practical applications, we believe that MPI will not scale to practical smart camera networks. We believe that a new middleware architecture that emphasizes real-time communication is necessary to build deployable smart camera systems.

Impact: These results justify the design of a new middleware communication mechanism that is better suited to peerto-peer, real-time communications.

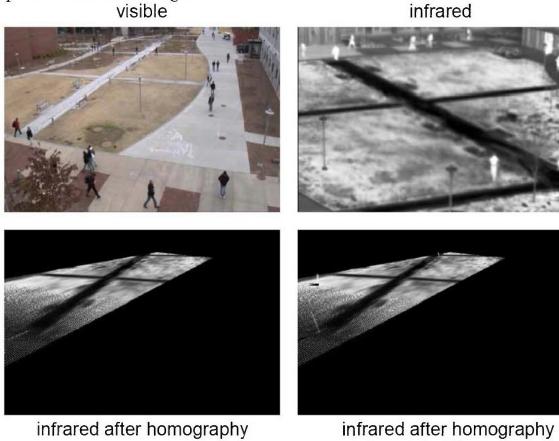
Result: We developed a new hardware architecture for real-time, embedded background elimination. This system implements mixture-of-Gaussian background elimination. It runs at 30 frames/sec on an FPGA platform.

Based on our experience with the FPGA implementation, we plan to experiment with the TI DaVinci processor as a platform.

Impact: This architecture could lead to new embedded systems for computer vision.

Result: We developed new methods for fusing data from unaligned visible and infrared cameras. This technique uses a combination of two techniques, homography and pseudo-3D transformations, to transform the images into a common global image space. Homography is used first to transform the infrared image to align its ground plane with that of the visible image.

A simplified 3-D model is then used to erect the target off the ground plane so that it more accurately corresponds to the target's position in the visible image.



and pseudo 3D

Figure 4: Alignment of images from separated visible and infrared cameras.

Figure 4 shows the results of a test of the algorithm on images from physically separated cameras. Our initial results show a slight improvement in precision over traditional fusion. We continue to work on these results.

Impact: This technique allows us to make use of infrared cameras that are not paired with visible cameras. Optically aligning visible and infrared cameras is bulky and expensive. Unaligned camera methods will allow us to deploy infrared cameras in more realistic environments.

Result: We developed a multilevel Bayesian network model for multi-band image fusion. Each band has its own image attributes---size, aspect ratio, color, brightness, etc.---which can then be fused by additional levels of Bayesian models. Our model, shown in Figure 5, is based on the multilevel Bayesian model of Singha.

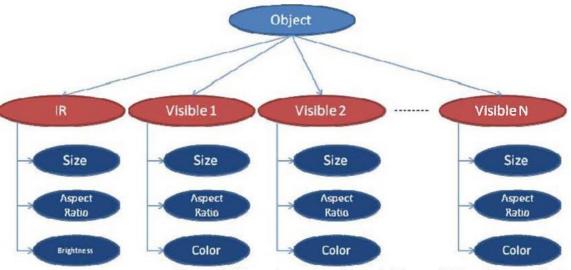


Figure 5: Bayesian network model for multi-band image fusion.

In Figure 5, the first level is the object level, the detected blobs are classified if they are objects. The second level is the camera level including an infrared camera and some visible cameras, we collect the probabilities from all cameras in this level. The third level is the features level, we calculate the probabilities of all features of the blobs in each camera. We expand Formula 4 as following:

$$\begin{split} P(Object \mid D, \xi) &= w_{IR} [P(Object \mid IR, \xi) P(IR \mid D, \xi) + P(Object \mid \overline{IR}, \xi) P(\overline{IR} \mid D, \xi)] \\ &+ w_{VS_1} [P(Object \mid VS_1, \xi) P(VS_1 \mid D, \xi) + P(Object \mid \overline{VS_1}, \xi) P(\overline{VS_1} \mid D, \xi)] + ..., (5) \end{split}$$

$$\begin{split} P(IR \mid D, \xi) &= w_{\text{size}}[P(IR \mid \text{Size}, \xi)P(\text{Size} \mid D, \xi) + P(IR \mid \overline{\text{Size}}, \xi)P(\overline{\text{Size}} \mid D, \xi)] \\ &+ w_{AR}[P(IR \mid AR, \xi)P(AR \mid D, \xi) + P(IR \mid \overline{AR}, \xi)P(\overline{AR} \mid D, \xi)] \\ &+ w_{B}[P(IR \mid B, \xi)P(B \mid D, \xi) + P(IR \mid \overline{B}, \xi)P(\overline{B} \mid D, \xi)], (6) \end{split}$$

 $P(VS \mid D, \xi) = w_{Size}[P(VS \mid Size, \xi)P(Size \mid D, \xi) + P(VS \mid \overline{Size}, \xi)P(\overline{Size} \mid D, \xi)]$ + $w_{AR}[P(VS \mid AR, \xi)P(AR \mid D, \xi) + P(VS \mid \overline{AR}, \xi)P(\overline{AR} \mid D, \xi)]$ + $w_{C}[P(VS \mid C, \xi)P(C \mid D, \xi) + P(VS \mid \overline{C}, \xi)P(\overline{C} \mid D, \xi)], (7)$

where Equation 5 is for the first level, Equation 6 is for the infrared camera on the second level, Equation 7 is for the visible camera on the second level. Object means the detected blob is classified as an object and W is the weight. IR means the infrared camera agrees the detected blob is an object. On the other hand, $\Box R$ means the infrared camera disagrees that. V S, Size, AR (aspect ratio), B (brightness), and C (color) mean in the similar ways. To simplify the model, we set thresholds for size, aspect ratio, brightness, and color for classification.

Preliminary results show that this model reduces precision somewhat but improves both recall and F-measure.

Impact: A more general model for multi-band image fusion has two advantages. First, it should help reduce our dependence on optically aligned sensors since each band is responsible for identifying its own features. Second, it provides a framework that should allow us to integrate new modalities.

Result: We developed improved methods for target monitoring. ID agreement adopts Markov Chain Monte Carlo (MCMC) method by utilizing object kernel histograms and motion vectors. We use a threshold to determine whether the entering object is new or not. The object ID with highest score which is bigger than threshold would be assigned to the entering object.

In Figure 6, each column picture is from the same camera and different frame. As new object enters camera2, system assigns it a new ID (004). After camera2 check with camera1 using MCMC, camera2 assigns the object an accurate ID (002), the same ID in camera1.

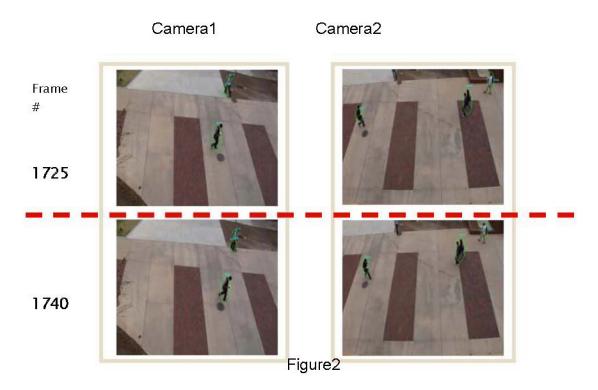


Figure 6: MCMC-based target identification.

Awards

Wolf received the IEEE Circuits and Systems Society Education Award in 2006.

Wolf was named Rhesa P. "Ray" Farmer Distinguished Chair and Georgia Research Alliance Eminent Scholar at the Georgia Institute of Technology. This chair was established to promote embedded computing; the Georgia Research Alliance component promotes entrepreneurship and technology transfer. Sample press releases on the appointment:

http://www.gatech.edu/news-room/release.php?id=1346

• http://www.gra.org/uploads/newsarticle/Wayne%20Wolf%20Press%20Release%20-%20Final.doc

Wolf received an honorary doctorate from the University of Patras, Greece in October 2008.

Publications

- S. Velipasalar, J. Schlessman, C. –Y. Chen, W. Wolf, J. P. Singh, "SCCS: A Scalable Clustered Camera System for Multiple Object Tracking Communicating via Message Passing Interface "IEEE International Conference on Multimedia & Expo, July 2006.
- S. Velipasalar, C. H. Lin, J. Schlessman, W. Wolf, "Design and verification of communication protocols for peer-topeer multimedia systems "IEEE International Conference on Multimedia & Expo, July 2006.
- Cheng-Yao Chen and Wayne Wolf, "Background modeling and object tracking using multi-spectral sensors," in *Proceedings, ACM Workshop on Video Surveillance and Sensor Networks, ACM, 2006.*
- Jason Schlessman, Ikdong Kim, Jaechang Shim, Yun Cheol Baek, and Wayne Wolf, "Low power, low cost wireless camera sensor nodes for human detection," in *Proceedings, Sensys 06*, ACM, 2006.
- Cheng-Yao Chen, *Distributed Multi-Modal Human Activity Analysis*: From Algorithms to Systems, Ph.D. Dissertation, Princeton University, August 2007.
- Senem Velipasalar and Wayne H. Wolf, "Frame-level temporal calibration of video sequences from unsynchronized cameras," *Machine Vision and Applications Journal*, DOI 10.1007/s00138-008-0122-6, January 24, 2008.
- Senem Veliapasalar, Jason Schlessman, Cheng-Yao Chen, Wayne H. Wolf, and Jaswinder P. Singh, "A scalable clustered camera system for multiple object tracking," *EURASIP Journal on Image and Video Processing*, v. 2008, article ID 542808, 2008.
- Senem Velipasalar and Wayne Wolf, "Lessons from a distributed peer-to-peer smart tracker," *Elektrotechnik and Informationstechnik*, 2008, 125/10, 1-7.
- Jason Schlessman, Mark Lodato, Burak Ozer, and Wayne Wolf, "Heterogeneous MPSoC architectures for embedded computer vision," in 2007 IEEE International Conference on Multimedia and Expo, IEEE, 2007, pp. 1870-1873.
- We have filed a U.S. patent application (PCT/US2007/071501) on the SCCS system.

Collaborations and Leveraged Funding

This project leverages a DURIP grant awarded during this period. We have purchased several important pieces of equipment:

- Three long-wave infrared (LWIR) cameras from FLIR Systems.
- Two medium-wave infrared (MWIR) cameras from Sensors Unlimited/Goodyear.
- Three high-definition visible light cameras from Panasonic.

We have already used these cameras to create several very useful sequences.

This project leverages an NSF ITR project on distributed smart cameras. That project is conducted in partnership with the University of Maryland. As part of that project, we developed the first distributed smart camera based on our earlier work on single-camera gesture recognition.

We partnered with Yokogawa Electric to develop new architectures for embedded computer vision. We developed architectures for optical flow and background elimination. We also collaborated with Panasonic Research Labs in Princeton, New Jersey on distributed surveillance systems. We received technical support for their MWIR cameras from Sensors Unlimited/Goodrich in Princeton, New Jersey. We also held technical discussions with Noble Systems, a manufacturer of MWIR sensors. We received programming environments from Texas Instruments for use with their DaVinci processor.

We have leveraged the PI's startup package at Georgia Tech for financial support of additional students and equipment.

Students

Five Ph.D students were supported in whole or part by this project: Senem Velipasalar, Jason Schlessman, Cheng-Yao Chen, Ping-Chang Shin, Chung-Ching Lin, Tai-Ming Lin. Two graduate students, Cheng-Yao Chen and Senem Velipasalar, received his Ph.D. during this reporting period.

Two unsupported M.S. students worked on projects relevant to this program: Mihir Wagh (background elimination hardware), Palak Shah (MPI measurements).

Survey questions:

- Number of undergraduates funded: 0
- Number of funded undergraduates who graduated: 0
- Number of funded undergraduates who graduated with a degree in math/science/engineering: 0
- Number of funded undergraduates who will continue onto graduate studies: 0
- Number of funded undergraduates who will work for DoD: 0
- Number of funded undergraduates with 3.5 GPA: 0
- Number of undergraduates funded by DoD Center of Excellence: 0
- Number of undergraduates who will receive scholarship: 0

Technology Transfer

We have discussed possible infrared/visible projects with the Georgia Logistics Center, located at the Port of Savannah.

Future Plans

We plan to study distributed tracking algorithms using vehicle-based sensors. Solving this problem requires jointly estimating vehicle and target positions. We plan to develop new MCMC algorithms to perform this estimation in a distributed network of vehicle-based nodes.