Imager Based Sensor Networks for Understanding and Creating Behaviors

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Abstract— **In this vision paper we propose the creation of sensor networks based on custom designed multifunction imagers that can directly pick out events of interest from a scene. We argue that with a suitable learning framework such sensors have great potential for realizing sensor networks that can interprete and subsequently orchestrate behaviors in physical space. This paper provides an overview of the research challenges followed by a brief description of our current research efforts towards creating a functional experimental system for investigating these intelligent networks.**

I. INTRODUCTION

The last few years have experienced remarkable progress in the field of sensor networks. Many pioneering applications have demonstrated that networks of tiny wirelessly connected devices can tremendously advance the scientific efforts to understand how nature works by providing information from places that were not reachable before [11], [24], [31], [4]. These efforts have also led to a better understanding for many of the architectural requirements of distributed sensor networks. Using such experiences as guidelines, we seek to develop imager equipped sensor networks that will become an ambient intelligent component for autonomously understanding and creating behaviors in physical space. We envision that the development of such networks will make the seamless provision of services possible, and in ways that will improve the quality of our everyday lives. Example applications of such technology are plentiful and range from training scenarios for sports, search and rescue operations, indoor games, security and safety.

In this paper we argue that the realization of such systems would be greatly facilitated by the successful development of two main components: 1) the creation of a distributed learning framework that is able to dynamically fuse multiple heterogeneous sensor measurements to interpret behaviors and 2) the development of integrated intelligent image sensors that can directly reduce an observed scene to a set of events. The integrated development of such intelligent imagers would result in devices that consume little power, have modest manufacturing costs, and more importantly simplify the way distributed learning frameworks function. This implies the ability of creating larger systems capable of providing high certainty predictions about behaviors, at low computation and communication costs.

We claim that imagers are a suitable technology to pursue for several reasons. First imagers very often provide qualitatively and quantitatively better information than other sensors. The can also have multiple functionalities allowing them to act as trigger sensors, motion and velocity sensors and as feature extractors. Our research vision is to combine a new custom imager sensor technology with the latest developments from computer vision with a variety of other smaller sensors to create an active sensor network that can detect complex behaviors in physical space. To do so we plan to pursue an integrative approach that exploits physical layer properties to build sensing functionalities in hardware that result in chaper, simpler, smaller and power power efficient sensors. These intelligent image sensors will be able to classify sensor data directly into a set of primitive events that can be directly used in a learning framework. This approach will essentially extract only the few useful bits of information at the sensor level, thus a minimizing the computation and communication requirements of the network. If successful this will provide a new approach for composing scalable systems capable of interpreting a wide range of behaviors in physical space.

In this vision paper, we first provide an overview of the research challenges (section II), followed by a description of our recent activities, towards developing a heterogeneous sensor network for interpreting behaviors. These activities include the development of an imager enabled sensor network and a custom multifunction imager architecture. Using these as starting points we aim for a new multifuction imager architecture that would serve as a building block the proposed behavior interpretation network.

II. RESEARCH CHALLENGES

A. The Application Perspective

A framework for learning behaviors with multimodal sensor networks equipped with intelligent imagers would benefit a large set of new applications, especially in the domains of security and safety. A sensor network for instance can be used in a building to determine group formation (i.e when groups of people come together and initiate conversation). A similar network can be used to detect the beginning of a fight inside a building, the delivery of packages or the unauthorized

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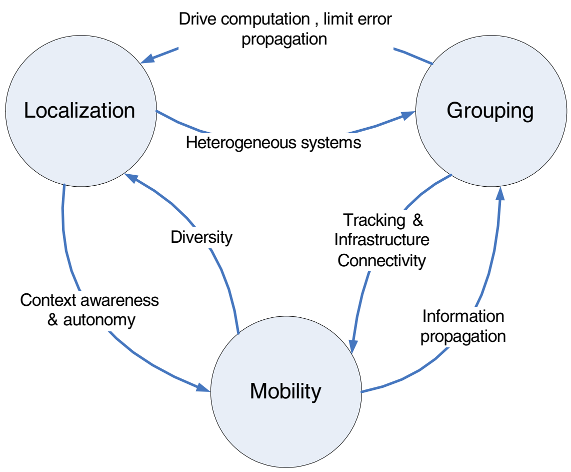

Fig. 1. Self-configuration components and relationships

removal of assets from a building. Safety applications also have a similar flavor. In these cases, a sensor network could monitor the workplace to ensure that certain work conditions are not violated. This would increase the safety of workers or ensure that expensive equipment is not damaged by improper use.

B. *Self-Configuration*

One of the main challenges for enabling sensor networks for interpreting behavior is the ability of the network to self-configure. Shortly after deployment, a distributed network should become context aware and autonomous. The network should be able to dynamically pick and choose from a wide variety of sensors at its disposal to reliably complete the task of sensing behaviors. To achieve this goal we are in the process of developing a suite of self-configuration services and a set of application support constructs that will form the alphabet for understanding and creating behaviors in space and time.

For self-configuration, we focus on three closely interrelated components of self-configuration: i) *localization and related calibrations*, ii) *grouping* and iii) *mobility*. The interrelationships of these components are outlined in Figure 1. Each of these components is closely affected by the operation of the others, hence we consider them jointly. Mobility for instance, can act as a source of diversity for localization. A moving node can be used as a reference for calibrating the location of other nodes, and can also potentially avoid obstacles in the signal path. By leveraging redundant measurements, non-line-of-sight components can be therefore filtered out. At the same location awareness allows nodes to move around space. Localization and mobility are also related to grouping. The grouping of nodes can help establish a leader based on geographical attributes if locations are known. Alternatively, one can group nodes according to vicinity information, a grouping that could also help nodes to localize themselves [37]. The role of sensors in self-configuration and mobility is further discussed in section V.

Application support constructs are methods for classifying a set of complex events that will form the alphabet for describing behaviors. Group formation for instance, can be an example of an application support construct for an indoor environment. In this case, the sensor network will recognize that a group of two or more people moved close to each other and started a conversation. A library of such constructs will allow the composition of applications that can sense and interpret behavior on a larger scale.

C. *Learning*

Several researches have invested significant effort, in understanding behaviors from sensor data during the past several years. Medical and activity researchers have focused on identifying characteristic motions of human activities, the sensors needed to identify those motions, and quantifying the energy expenditure of the users. Hierarchical hidden semi-Markov models (HHSMMs), specific types of Dynamic Bayesian Networks, have been used to track the daily behaviors of residents in an assisted living community [17]. Even nave Bayesian network structures have shown to be sufficient to recognize complicated behaviors involving the behaviors of 11 coordinated people given noisy input data [16]. In addition, tree-augmented Bayesian networks [12] have recently been used to recognize behaviors such as ”grocery shopping”, ”going to work” and ”doing laundry” among others from GPS data.

For our research, we pursue the development of a distributed learning framework that can fuse events collected by customized networked imagers with measurements from other sensors. To make that happen we need to consider the type of sensor measurements that would be sufficient for learning and behavior, as well as what is a suitable training set that adequately train the network for this behavior.

D. *Power Efficiency*

Low power operation is indisputably a key ingredient that needs to be addressed by our integrated approach. From an energy perspective, hierarchical designs provide a sound approach. They provision for networks that have different energy levels, from ultra-low-power deep sleep modes, to fully functional modes. We note however that this unimodal consideration of energy conservation is not always sufficient. Sensor nodes still require a number of sensors and their corresponding software support. This however will increase size and production costs making these solutions ”difficult” for wider use. We advocate that the hierarchy should have an event driven functionality, directly applied into the hardware. Instead of collecting image sequences, image sensors should directly detect and classify a set of complex events such as motion, velocity, direction of motion, change in the light conditions, tracking, image acquisition and low bandwidth video acquisition. This feature extraction capability will autonomously drive the sensor through different operational modes with different power requirements as needed. Imagine for instance an integrated image sensor that acts as an ultra-low-power trigger sensor. Such a sensor will consume microwatts of power while in ”trigger” mode. When motion is detected in a scheme the sensor can switch to a more complex level of operation to estimate, the direction and velocity of motion. Later on it can also track various entities or people in space.

The sections that follow outline our current research activities in new imager architectures, sensor network testbeds and the simultaneous node localization and imager calibration.

III. New Imager Architectures

In a sensor network requiring an image sensor as front-end detector, commercial off-the-shelf (COTS) image sensors are far from being the optimal choice. COTS are not able to efficiently extract features in a scene, because they *blindly* collect all the visual information whether the scenes contains new and useful data or not. Image data is notoriously large even for small image sensor operating at video rates (33fps). As an example a VGA sensor generates 2.4Mbits/s. In sensor network application aimed at understanding behavior the information sought are often very few bits, usually 1 bit: is there a person in the scene? Is there motion in the scene? We therefore believe that a sensor network that recognizes behavior cannot be implemented without efficient sensing of events, rather than bits. Furthermore, if data reduction is not performed at the sensor level, vision algorithms must be used to extract features from an image [18], [5], [33]. In this case, the amount of computation to extract features from the visual data is practically always too high for the limited power budget of a sensor network node. This is the reason that a wealth of research is underway to develop new protocols for communication in wireless sensor networks that are energy aware [36]. In this context we propose the use of an ultra-low-power image sensor that can detect specific features of interest. Our image sensors (named ALOHA) use a spike-based digital representation of the image data to encode and compress information. They use less power than conventional image sensor because they only output the relevant information (intensity of brightest pixels, motion, contour) as opposed to entire frames. We will here describe our initial prototypes of efficient image sensor that encode light intensity into a frequency of events.

A. Address Event Camera Technology

In a distributed processing system, when there is a-priori knowledge that not all nodes are likely to require computation and communication resources at the same time, a fixed time-slot (synchronous) allocation of resources among all nodes is wasteful. If the demand for resources is bursty, computation and communication can be done asynchronously. The image sensors presented here utilize an asynchronous event-based digital representation (AER) of information originally proposed by Mahowald and Sivilotti [22], [27] and subsequently re-engineered by Boahen [3]. In the AER terminology, *events* are communication primitives sent from a sender to one or more receivers. For an image sensor, events are individual pixels reaching a threshold voltage and accessing the bus for communication with an outside receiver. An AER image sensor is composed of an array of pixels, and the digital output of the image sensor is the address of the pixel that is to communicate an event (refer to Figure 2). The integration time of each pixel varies in relation to the incident light intensity. Since the activity of the array is generated by the light intensity of the scene, and not an external scanning circuitry, the rate of collection of frames can be modulated by varying the *request-acknowledge* cycle time between the imager and the receiver circuitry. *Thus information can be extracted on demand from individual nodes in a wireless sensor network.* The address-event representation of an image can be thought as a realization of a delta-sigma pixel-parallel analog to digital converter [21]. In this paradigm the output of the ALOHA image sensor is a sequence of delta-sigma conversion, identified by the addresses of individual pixels. Thus the output of each pixel of the image sensor is always 1bit and is only communicated when enough light (information) has been collected. This corresponds to a dynamic allocation of the output bandwidth determined by *need* as opposed to scanned sensors, which allocate uniformly and inefficiently the bandwidth across pixels. Thus, representing intensity in the time domain allows each pixel to have large dynamic range [6], [29], [10], [38].

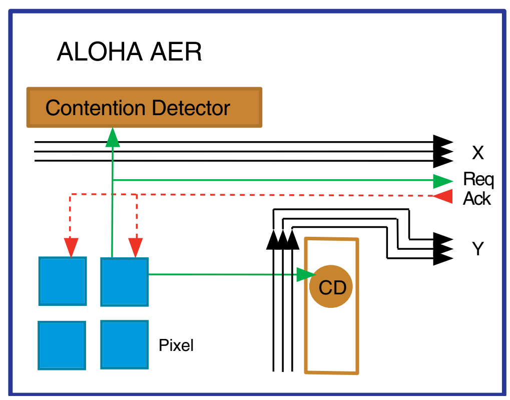

Fig. 2. ALOHA image sensors architecture. A pixel generates and event, the event generates a request (*Req*) and outputs the pixel X, Y addressed on the output bus. A collision detector circuit detects multiple rows or columns trying to access the output bus at the same time. The receiver circuits responds with an acknowledge (*Ack*) as a confirmation of detecting the event and reading the image sensor output bus.

B. The ALOHA Image Sensor

A conventional electronic image sensor integrates light in a matrix (frame) of sensors (pixels). Each frame is scanned by addressing each pixel in a row and each column. The pixel data is transferred to a ’video memory’ and then the frames are processed by the sensor node microcontroller to extract features. The Cyclops module [26] for MICA motes developed by UCLA and Agilent is an example of this effort. To prevent overloading the sensor node processor, the Cyclops design employs an external processor a CPLD, SRAM and

FLASH memory, offering CIF-resolution image processing at the expense of large power consumption (excess of 50mW). Standard COTS camera module, although often labeled 'low-power' (referring to the tens of mW range), consume large amount of power when compared to photo-transduction limits. Just a few notorious examples are: 15mW for the SMaL sensor IM-001 Series [28], 54mW for the Micron MT9V012 [23], 80mW for the Agilent camera module ADCM-1650-3011 [1]. The power consumption is attributed to the relatively high resolution of the sensor, color processing, compression, multiple readout and interfacing standards. All of these features are of little significance to sensor network nodes, where low power consumption is instead a much more desirable feature. COTS modules can last only 1 day running on two AA batteries, while measured data from custom image sensors in research papers yields 6 days [21], 13 days [7], and 4.5 years of our most recent prototype [9]. Our second-generation prototype camera [34] is a CMOS image sensors with digital output fabricated in a 0.6m CMOS process. The imager performs a light-to-frequecy conversion at the pixel level. The four quadrant, 32 x 32 pixels image sensors present very high dynamic range and ultra-low power operation targeted to energy aware sensor network applications. Two samples collected, respectively of the 'analog devices' sign and President Jackson of a 20 dollars bill are reported in Figure 3. The image sensors produced approximately 10,000 events in a period of 1375ms, while the current consumption of each quadrant for this output event rate was $2.5\mu A$ at 3.3V. This corresponds to a power consumption of $5.75\mu W$ for each quadrant of [name witheld], a value that would scale to $60\mu W$ for a VGA size. With this power consumption [34] can run on two 1000mAh AA batteries for 4.5 years!

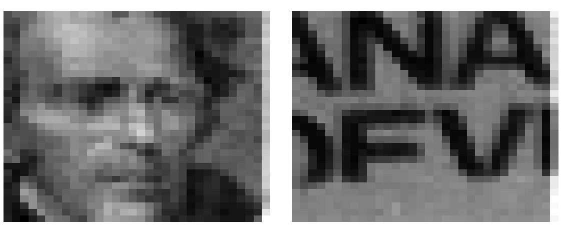

Fig. 3. Example images collected with image sensor ALOHA. President Jackson and 'Analog Devices' text.Images were collected with the sensor operating at 7.6Kevents/s.

C. Camera Enabled Sensor Nodes

Our first image sensor system architecture aimed at active illumination for sensing and synchronization in distributed imagers for sensor networks. The system employs an event based image sensor (*ALOHA* imager) [9] and COTS motes forming a sensor network [8] using standard *TinyOS* software interfaces. Our system provides active illumination of the scene by making use of the sensor network infrastructure, thus capturing relevant data only when required [2]. Our wireless image sensor network with active illumination is composed of an address-event image sensor, a prototype interface board, a transmitting wireless node and one or more additional motes acting as illumination sources. Figure 4 shows a schematic representation of such system, with a single *MicaZ* mote from Crossbow, broadcasting data from the image sensor to a base station comprised of another *MicaZ* mote connected to the receiving computer.

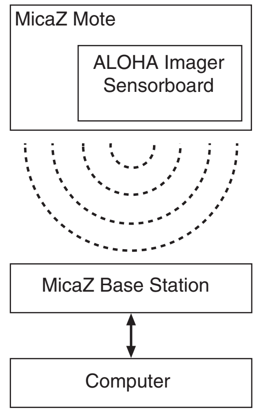

Fig. 4. A schematic of the prototype system.

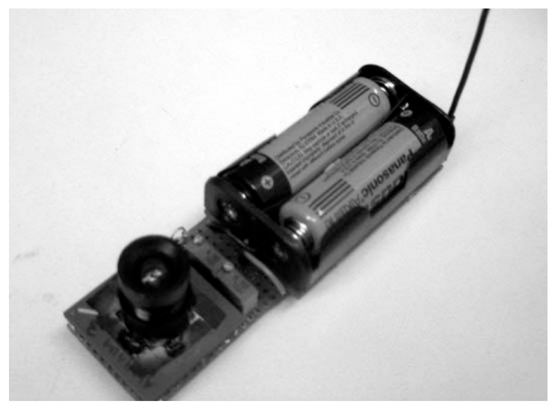

Fig. 5. MicaZ mote with imager sensorboard.

A system-specific sensorboard was fabricated in order to interface the mote to the image sensor (see Figure 5). The sensorboard also contains a voltage regulator and passive components used to power the image sensor. With our setup (first generation system) each node is capable of transmitting a 32×32-pixel array in an address-event fashion, robust against packet-shuffling and loss. In our tests we achieved a frame rate of 6fps when using 500 events to generate a frame. This is close to the expected rate of $0.19fps$, which is a measured limitation of the *MicaZ* mote. These values will be easily improved by supporting newer motes as they become available. Given that the whole system runs under the TinyOS platform, hardware upgrades are virtually plug-and-play. Our next generation cameras are interfaced to a new more powerful sensor node as part of a larger testbed, described in the next section.

IV. Sensor Network Testbed

To experiment with learning behaviors from heterogeneous sensor networks we have constructed a multimodal sensor network testbed that is deployed inside the computer science building and the Morse Teaching Center at Yale. The testbed is comprised of 50 custom designed XYZ sensor nodes [20] designed for mobility and learning applications. Half of the nodes are deployed on a 3 dimensional testbed installed in a single room. The rest of the nodes are deployed across a busy corridor in the Morse Teachning Center that connects the computer science building with the engineering building at Yale. This testbed features a heterogeneous set of sensors including imagers, passive infrared (PIR), light, temperature and acoustic sensors.

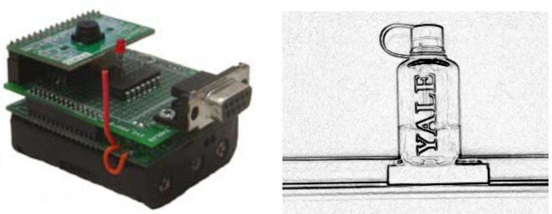

Fig. 6. XYZ sensor node with COTS camera module, with a captured image after sobel edge detection

The XYZ sensor nodes are instrumented with three different imager setups. The first one is a small board based around a COTS camera module from Omnivision (Figure 6. This is used for acquiring images over the network and for small prototyping. The second is a custom interface to the ALOHA address-event camera prototypes described in section III. Our prototype is shown in Figure 7. The third is also based on the COTS camera module but with the camera attached to a more powerful embedded DSP processor capable of more powerful computation. This third setup is used to prototype more computation demanding vision algorithms but also to model the operation of the spike camera in software. Some of the camera enabled sensor nodes are described in the next subsection.

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The XYZ sensor nodes run SOS, a lightweight operating system, that supports dynamic module loading and unloading at runtime [13]. This provides a powerful development tool

Fig. 7. XYZ sensor node with ALOHA imager (camera lens removed)

that allows us to update the applications running on our testbed from a remote locations. Furthermore, it provides a flexible framework to start developing the proposed learning applications using real data and real-time operation.

V. Localization and Camera Calibration

This section describes our initial work on combining image information with sensor measurements to perform node localization and camera calibration. This is a function that falls under the umbrella of self-configuration described in section II-B. Cameras need to calibrate their views with respect to the views of their neighbors and must also be able to localize smaller nodes with non-imager sensors.

Our initial efforts in this direction have focused on establishing a relative reference frame in which neighboring cameras can compute the relative rotations and translations with respect to each other, and at the same time localize other nodes found in the common field of view of other camera pairs.

To bypass the correspondence problem among multiple camera views, sensor nodes need to create sensing stimuli that uniquely identify themselves to the cameras. This can be done by programming each node to broadcast its ID using an omnidirectional LED. The cameras can then acquire multiple frames from each vantage point to uniquely determine the image coordinates of each node. If these coordinates are known, it may be possible to compute the three dimensional coordinates of the observed nodes. Since camera information alone cannot provide any depth information about a scene, we also use a limited set of distance measurements between nodes to determine a coordinate system in Euclidian scale.

Instead of using computationally demanding methods from computer vision that require factorization such as [35], [25], [30] , we focus on determining the coordinate systems between camera pairs using the camera epipoles. The epipoles between a pair of cameras are defined as the points where a straight-line connecting two camera centers intersect at the image plane of each camera as shown in Figure 8 [15]. If the epipoles between a pair of cameras are known, then the relative rotations between the two cameras, can also be computed.

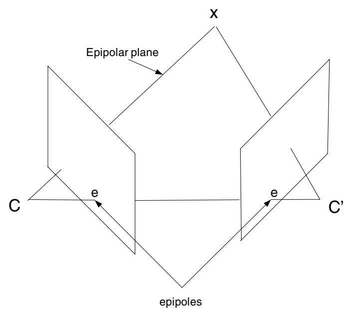

Fig. 8. The epipoles between a pair of cameras

Also if the relative rotation and translations between a pair of cameras is known along the path, the one can easily compute the coordinate transformation that would bring all the nodes in the same coordinate system.

To make use of epipoles on a distributed sensor network, our work considers two possible methods, measured epipoles (ME) and estimated epipoles (EE), described in more detail in [19]. Measured Epipoles builds on a method proposed by Taylor in [32], and requires that two cameras nodes can observe each other and must have at least one node in their shared field of view. If these conditions are met then the relative rotation between the two cameras can be computed. The ratio of distances of the triangle formed by the two cameras and a node can be computed using the previously computed rotations between the cameras.

If a pair of cameras cannot directly measure their epipoles, it may still be possible to estimate the epipoles if they have a sufficient number of nodes in their shared field of view. To solve this problem we use the eight point algorithm prosposed by Hartley in 1997 [14]. EEs are typically noisy and further refinement is needed. Figure 9 shows a comparison of ME and EE using our experimental imager network. The Figure shows error on distance estimates from a camera node to a group of other nodes when ME and EE are used. ME is relatively accurate and close to the ground truth measurement. EE is less accurate and requires additional refinement between the two corresponding pairs of views. Although this accuracy can be improved with standard methods from computer vision such as stratification [15], we are seeking to develop more lightweight methods that are computationally lightweight and can run on resource constrained sensor nodes.

VI. Conclusion

In this paper paper we motivate the use of imager based sensor networks for understanding and creating behaviors. To realize these networks, we identified two main research directions, a distributed learning based framework and a custom multifunction imager. We have also described some of the hardware infrastructure towards achieving this goal. In the near future, we will provide a closer treatment of the learning based framework. Up-to-date information on this effort can be obtained from our website at http://www.eng.yale.edu/enalab.

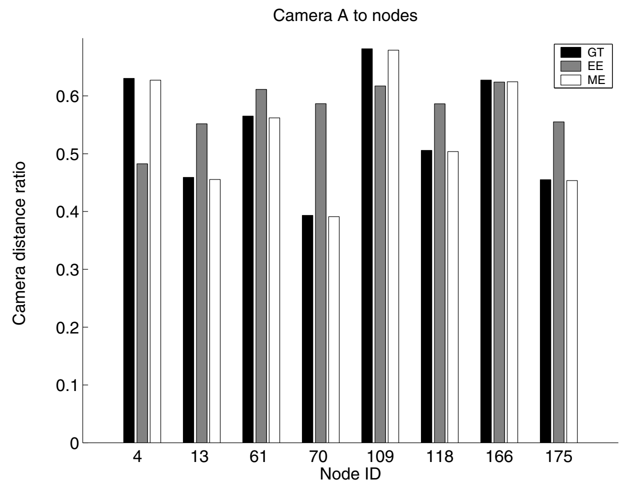

Fig. 9. Comparison between EE and ME

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