WIRELESS INTEGRATED NETWORKED SENSORS: SIGNAL SEARCH ENGINE FOR SIGNAL CLASSIFICATION

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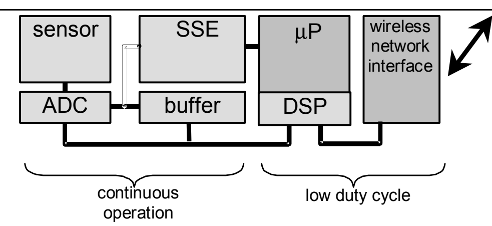
ABSTRACT

Wireless Integrated Network Sensors (WINS) provide a distributed monitoring approach for battlefield situational awareness, machine condition based maintenance, health care, transportation, and other applications. The WINS architecture is based on compact, intelligent, networked low-power sensor nodes. WINS operation relies on efficient system design and low power event classification with resulting applications. Efficient system design with power constraints facilitate scalability for a distributed sensor network. Low power design must accommodate signal processing and event classification from multiple-type of sensed signals. This paper presents a flexible, and scalable method of signal classification designed for WINS. Signal Search Engine (SSE) with the time domain classification method relies on template matching using templates derived directly from field measurements. An enhanced hybrid-SSE with the use of 'wavelet' method classification is also described. Results obtained from the time domain signal classification scheme and the 'wavelet' method give error rates of less than 15% with minimal signal pre-processing.

INTRODUCTION

Wireless integrated network sensors (WINS) combine sensing, signal processing, decision capability, and wireless networking capability in a compact, low power system.[1,2,5] Compact geometry and low cost allows WINS to be embedded and distributed at a small fraction of the cost of conventional wireline systems. WINS defense applications include battlefield situational awareness for security and tactical advantage. WINS also provide distributed condition based maintenance for vehicles and energy systems for enhancements in reliability, reductions in energy usage, and improvements in quality of service. Many new applications are expanding in the consumer domain for decision support systems as well.

WINS sensor distribution, enabled by the WINS low power architecture, provides improved event detection and classification capability. Since WINS nodes are low cost elements, they may be distributed on a dense spatial scale. This ensures that separation between nodes and source signals are minimized. Reducing distance between source and node results in both increase in source signal to noise ratio (SNR) and reduction in signal distortion during propagation of seismic or acoustic signals. Closely spaced sensors further provide optimized low power wireless communication of data and decisions. Multi-hopped wireless data communication add to optimized low power data transmission in addition to enhanced battery life and sensor node life-time. [6]



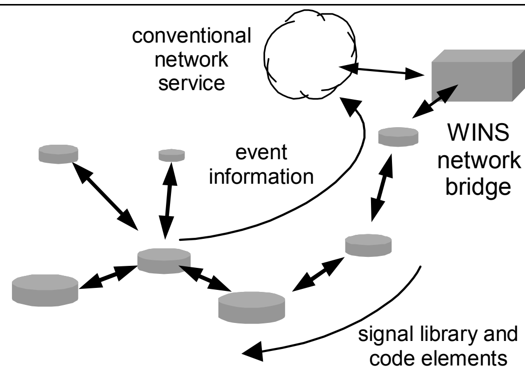
The wireless integrated network sensor (WINS) node architecture includes sensor, data converter, signal processing, and control functions. Micropower RF communication provides bidirectional network access for low bit rate, short-range communication. The micropower components operate continuously for event recognition, while the network interface operates at low duty cycle. The prototype SSE is resident in the node processor. Future implementations of the SSE can operate as an independent coprocessor.

Figure 1

The opportunities for WINS depend on the development of a scalable, low cost, sensor network architecture. This requires that sensor information be conveyed to the user at low bit rate with low power transceivers. Continuous sensor signal processing must be provided to enable constant monitoring of events in an environment. Thus, for all of these applications, local processing of distributed measurement data is required with a low cost, scalable technology. Hence, the signal search engine (SSE) is developed with the intentions of local on-board, low power, robust event classification.

WINS ARCHITECTURE

The WINS architecture includes a distributed sensor network that may provide a link between large-scale networks (for example, long range battlefield wireless networks or global Internet services) and local physical measurements. The WINS architecture is based on WINS nodes (see Figure 1) carrying sensing, signal processing [3] and communication functions.



WINS nodes (shown as disks) are distributed at high density in an environment to be monitored. Multihop communication permits low power operation of dense WINS sensor networks. WINS node data is transferred over the asymmetric wireless link to an end user or to a conventional wireline or wireless (IP) network service through a WINS network Gateway. The WINS Gateway manages the network and provides a network protocol translation. SSE library and code information flows to the nodes, while derived events and data flow to the remote user.

Figure 2.

The WINS network architecture, shown in Figure 2, is based on messaging with minimal use of power or bandwidth resources. The architecture includes sensing elements (nodes) and a network bridge that provides both local network monitoring and control, and functions as a protocol translator. The architecture relies on methods that:

- Acquire physical measurements at the nodes.
- Classify events at the nodes (on-board).
- Communicate short event codes (rather than unprocessed data).
- Perform low power collaborative decision fusion.
- Catalog, and warehouse decision and relevant information to be referred by decision-support systems.

In addition to event decisions flowing towards remote users, reconfiguration data and code elements flow from the users to the nodes. In particular, for the SSE, this information includes signal library elements and updated classification code modules, in addition to networking, routing, and decision fusion protocols. Consequently, control functions that give more robustness and modularity into decision-fusion modules and networking protocols are transmitted by the user to individual nodes, and cluster heads.

DISTRIBUTED SENSOR SIGNAL CLASSIFICATION

Operations of sensors in field conditions reveal a number of challenges for signal event classification. Specifically, variation in the node deployment environment and topology yields distortion and SNR variations of event signals. In addition, variation in source motion yields a rich variation in signal characteristics. Finally, many important events produce complex and short impulse signals that contribute to a variation of wideband signals that come from moving sources. These characteristics have guided the development of an SSE that permits comparison of unknown event signals to a template library of stored event templates. Time domain, and wavelet classification is utilized to accommodate analysis of short impulse signals and a variety of wideband signals measured from real world situations.

Distributed sensor signal processing can exploit network communication to enhance the performance of local node signal processing. In particular, the network can offer programmability in addition to having multi-hop transmission optimized for low-power wireless communication of data and decisions. The benefit of this feature is explained here: In the event that a node (or a collective group of nodes) is unable to identify an event among a library of templates, or if confidence measure attained from the decision are below a certain threshold it will be required that a selected set of time series data, associated with the event, be propagated through the network to a cluster head or remote user (for analysis by a more powerful processor / system). Alternatively, in the case of sensors having storage space, time series segments are saved for later inclusion into the sensed signal database or for off-line classification. To avoid the high-energy dissipation associated with such an error, remote reconfigurability must be applied. A hybrid SSE further facilitates a choice between dual classifications in the form of a wavelet or other transform domain approach. For corrective action, the network is exploited, to download new signal processing data to enable future detection of this event.

Distributed signal processing systems must also have the attributes of

- Protocol reconfigurability (allowing node and network operation to be optimized for varying conditions by remote control).
- Scalability to enable increasing network scale without requirements for changing the existing network architecture.
- Compatibility with low power operation.
- Low power wireless communication for decision-fusion and transmission to the end-user or decision support system.
- A hybrid SSE to re-inforce or re-classify low confidence decisions.

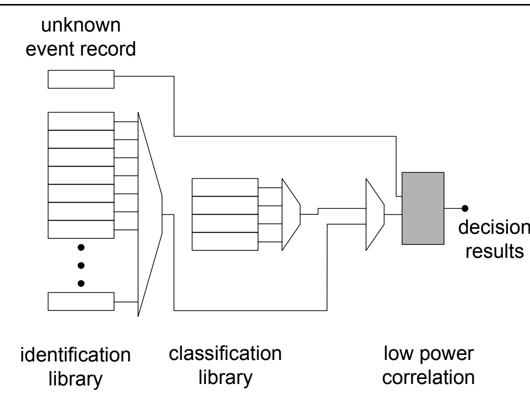
SIGNAL SEARCH ENGINE

Time domain processing is applied to the event classification problem. Additional wavelet methods have proved to be promising for event classification proving worthwhile for a hybrid - SSE. The WINS frequency domain signal processing system has been described previously.[3] Time domain signal processing based on state-spaces is particularly important for wideband sources while proving to be highly accurate. A combination of acoustic, and seismic signal classification and eventual fusion of decisions have made it more favorable for multi-type signal search engine (M-SSE).

The basic SSE architecture is shown in Figure 3. This module is extended with signal pre-processing and decision fusion architectures for on –board or collaborative decision-making at a cluster-head node. The SSE compares unknown event records with stored library tree of signal templates using a low power correlator. Operation of the SSE begins with the selection of a set of signal library elements (templates). These templates are short data packets (length of 10 – 100ms) selected *directly* from time domain samples of field records during signal classification training. Signal classification is performed with sensed signals that are classified with assignments of associated confidence measures. Local interim decisions and confidences are fused on board exploiting state-spaces. Decision fusion focuses on fusion methods that include maximum polling and weighted averaging. A high value in confidence measure indicates the unknown signal probably comes from the same class as that of the representative library template.

The SSE operation is optimized for signal classification through selection of: 1) selecting distinct features of correlator time series segment, 2) the correlator segment length, 3) the window stepping period for RMS averaging, 4) filtering and sub-sampling of the correlator and data series. The optimizations of these parameters are completed during training, prior to the initial configuring of the WINS node.

The SSE offers the features discussed above for network signal processing. First, the SSE architecture is programmable. It is immediately clear that the SSE signal library may be edited to add or subtract templates from the search space. Reconfigurability can also be provided by allowing remote network control of search priority and depth.



A schematic view of the Signal Search Engine (SSE) architecture. The SSE compares unknown event records with stored library signals using a low power correlator. A hierarchy of signals may allow signals to be first classified, and then identified. The hierarchical search lowers the number of computations required to arrive at classification. In addition, the benefits of energy expenditure as a function of improved classification accuracy may be estimated and used to manage node energy.

Figure 3

The SSE is also compatible with scalable network architecture. Here signal library templates may be propagated throughout the network. In the circumstance that an event may not be identified (even with the hybrid

SSE), and only intervention by a remote operation is successful, then a new signal library element is supplied to all nodes in the network.

Finally, the SSE offers low power operation through a hierarchical search method. The hierarchical search may allow signals to be first classified, and then identified. Here, an unknown signal is initially tested against a limited family of correlators with the intention of detecting the class of origin of the signal (for example, from the class of wheeled or tracked vehicles.) The classification of the signal class may itself be a valuable result. However, as called for by the node protocols, a more intensive search may be executed on the family members (child nodes) in the derived class tree structure. The hierarchical search minimizes the number of computations required to arrive at a more precise classification. In addition, the benefits of energy expenditure as a function of improved classification accuracy may be estimated and used to manage node energy.

The correlation operation defined here may be compared with conventional filtering. The correlator forms an anti-causal FIR filter. Coefficients of this filter are, in turn, derived directly from actual field data. Low power operation for the SSE should be expected due to demonstrated operation of micropower digital filters. [3, 7, 8]

SIGNAL SEARCH ENGINE IMPLEMENTATION

A prototype SSE has been implemented in software (code implemented in C++) operating on a general-purpose processor (Pentium PC). Additional features for state-space based classification are built for a proto-type operation of the SSE on the same platform. This software test bed has been applied to a library of acoustic and seismic records obtained from field data acquisition testing of WINS acoustic and seismic sensors for tracked and wheeled vehicles.

The SSE was subjected to a typical test including unknown signals obtained during field measurements on a tracked vehicle and a wheeled vehicle. The correlator itself is a record taken from one of the vehicle data sets that is not used in the test signal set. Results of the SSE show robustness to phase noise content giving validity for a generalized template tree for array-sensor data. Efforts are concentrated on obtaining an optimized tree with associated probabilities attached to each leaf node. Results from SSE show correct classification for low SNR signals showing SCIA algorithm robustness to noise. The SSE results are dependent, as expected, on the selection of the proper template (equivalently, matched filter coefficients). Detected signals are eventually calculated for confidence measures after which decisions are fused on board and transmitted for further collaborative decision-fusion at a cluster head. Decision fusion is obtained through state dependent modules from each type / class of sensed signal waveform. Investigations reveal that fusion methods are dependent on the node architecture and are implemented on a case-by-case basis for individual node topologies and sensing criteria.

SSE EVALUATION

Acoustic signals from the Army Research Lab (ARL) ACIDS database for a selection of tracked and wheeled vehicles were used to "train" and test the SSE. (Signal content used for training the SSE was removed from the signal sets used for evaluation.) Then, a matrix method was formed where the matrix element values correspond to the RMS values of the template-signal inner products. The

SSE matrix may now be examined to determine and predict SSE performance.

Figures 4 show examples of these results. In this figure, the RMS amplitude of the correlator-signal inner product is shown for inner products between all signals and templates. The set of these inner product RMS amplitudes forms a matrix with the matrix element scalar value being the RMS signal amplitude. Ideal SSE operation occurs where the RMS value of the inner product between a signal and a template are maximal for the case where the template correctly identifies the signal. Thus, ideal operation yields a matrix where the diagonal elements are greater than any off-diagonal element in the same row or column as any diagonal element.

The SSE has demonstrated the ability to identify the differences between signals generated by a source for the approach, departure, and closest approach signal segments. In the event that proper templates are available in the SSE library, this sensitivity to the evolution of an event signal may be exploited for enhancing source classification accuracy.

A result from a similar dataset using the wavelet method is given in Figure 5. Here classification is performed on the signals using the class representor method (CRM). Recorded source signals were initially normalized to remove any dependency of the signals to the gains in the sensors. This in effect gave an equal weight to each of the training signal especially when no apriori knowledge was known of sensor calibration. A class representor to each pre-defined class was obtained. Figure 5 shows the results of classification with the CRM method in the Haar subspaces. A coiflet-5 wavelet with 5 levels of decomposition is used for this classification. For this case, the haar method results in 10.9% error while the complete method gives a 5.45% error. Signal pre-processing and a selective choice of signals for obtaining the representors during training obtain better classification results.

Wavelet methods have been chosen for hybrid SSE for enhancing classification re-inforcements, while serving as an alternative to verification of time domain SSE results. Selection of which method to activate as a generic while having the other on reserve depends on the sensed signals waveforms and WINS applications. Having obtained promising results from wavelet methods with minimum pre-processing, a hybrid-SSE implementation is considered with time-domain and wavelet method classification.

Class Representor Method classification of acoustic data signals from the arctic terrain in the Haar and Complete subspaces using the Coiflet-5 wavelet at 5 levels of decomposition.

Figure 5

CONCLUSIONS

A Signal Search Engine (SSE) architecture has been developed for time domain signal classification. A prototype SSE has been demonstrated with successful results. An SSE system level architecture study for the low clock rate correlation operation indicates it will yield micro power operation. [3] Wavelet method classification is introduced with increasing accuracy with the incorporation of signal pre-processing and state space decomposition. An initial investigation on the Haar and complete class representor method gives much promising results for a hybrid – SSE. Having formulated signal classification through the time domain SSE and possible implementation of hybrid-SSE with the wavelet method, less than 15% error rates were obtained during tests of measured data from each of these methods independently.

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