A Neural System for Structural Health Monitoring

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ABSTRACT

This is an overview paper that discusses the concept of an embeddable structural health monitoring system for use in composite and heterogeneous material systems. The sensor system is formed by integrating groups of autonomous unit cells into a structure, much like neurons in biological systems. Each unit cell consists of an embedded processor and a group of distributed sensors that gives the structure the ability to sense damage. In addition, each unit cell periodically updates a central processor on the status of health in its neighborhood. This micro-architected synthetic nervous system has an advanced sensing capability based on new continuous sensor technology. This technology uses a plurality of serially connected piezoceramic nodes to form a distributed sensor capable of measuring waves generated in structures by damage events, including impact and crack propagation. Simulations show that the neural system can detect faint acoustic waves in large plates. An experiment demonstrates the use of a simple neural system that was able to measure simulated acoustic emissions that were not clearly recognizable by a single conventional piezoceramic sensor.

Key words: Neural System, Composite Materials, Structural Health Monitoring

1. INTRODUCTION

The performance and safety of advanced structures is dependent on the reliability of composite materials and heterogeneous materials. There has been a reluctance to deploy such high performance materials in critical structural applications because of their susceptibility to in-service damage. The damage occurring in these materials may be difficult to track and can propagate fast during operation of the vehicle or structure. Therefore, a material-integrated sensing system is needed to monitor and detect damage during vehicle operation. Such monitoring systems can revolutionize the way structural systems are currently maintained and enable users to determine at any time the functional and operational readiness of their equipment. Examining conventional non-destructive evaluation techniques [1-6] indicates they are labor intensive, expensive, and they are not designed for efficient integration into composite and heterogeneous structures. Autonomous integrated Structural Health Monitoring (SHM) techniques are needed to continuously monitor the condition of a structure, and are a revolutionary concept in the maintenance of structures. Various approaches for SHM use piezoceramic sensors and actuators [7-19] that require separate wiring connections for each sensor and actuator element, storage of pre-damage data for each sensor, and instrumentation for active generation and sensing of diagnostic vibration signals or waves. When the structural geometry is complex, has varying thickness, curvature, ribs, joints, heterogeneous materials, or the damage is near boundaries, it becomes difficult to detect small damage using these methods. In addition, the number of sensor circuits and computations required increases the complexity and cost of the structure. Another approach for damage detection is to integrate many fiber-optic strain gages within the structural material. An optical fiber with twenty or more Bragg gratings can measure static and dynamic strains at discrete locations on the structure. An optical analyzer can multiplex over each fiber and each grating to measure strains at a large number of points on a structure. This approach is being implemented on bridges, pressure tanks, and other structures. Fiber optic sensors have limitations when applied to monitoring complex composite structures where damage can occur in any layer and at any spatial location on the structure. The discrete strain measurements can miss damage because the measurement is very localized at the fiber/grating, the optical analyzer using
multiplexing and many connections is expensive, measurements are not simultaneous, and the frequency bandwidth may be too low to sense Acoustic Emission (AE) signals. The approaches discussed all have advantages for certain applications. A new approach is outlined next that has important advances (and some limitations) as compared to existing techniques.

There is a potential for the use of Acoustic Emission (AE) signals for SHM. AE sensors are currently suitable for detection of damage in structures at “hot spots.” The use of AE measurements for SHM of large structures has the advantage that it is a passive sensing technique that is simple and may be more practical than using active interrogation methods. A limitation is that AE monitoring can only be done when the structure is operating. Present AE and vibration monitoring techniques require bulky instrumentation with numerous channels, long connections, and centralized data analysis. These systems may be impractical to embed on the structure to operate in the field. Another limitation is that AE waveforms from such sensors are too complicated for purposes of source characterization. The open problem is: How can the sensor system be simplified and still provide sufficient spatial coverage to efficiently sense AE signals? A number of recent advances including the development of new piezoceramic fiber materials, micro-miniaturization of chips, damage modeling, embeddable software algorithms, and biomimetics have opened the exciting possibility for the design and development of micro-architected synthetic nerves capable of self-sensing and self-quantification of damage in advanced materials. This new multifunctional neural material can result in the realization of increased performance capabilities of structures, enabling lower cost, lighter weight, and increased reliability. This continuous sensor system works by mimicking a biological nervous system. The sensor system consists of an array of autonomous unit cells, each having several sensing elements and a neural processor that is capable of detecting and quantifying damage in its neighborhood. In addition, each of these neural processors will be capable of bi-directional communication with a central processor over a digital data bus. Conformable piezoceramic fibers will be used to form the distributed sensor elements. Key to the feasibility of the neural sensor is the development recently of continuous sensor technology [20] that has been demonstrated to make AE monitoring more practical on a large scale. This sensor concept can reduce the number of signal processing channels by a factor of ten or more while simultaneously improving the sensitivity and bandwidth. Further, the neural cells lend themselves to embedding in high-performance structural composites that are likely to benefit most from health monitoring technologies. This continuous, highly distributed sensor system can monitor large structural areas with a single digital data bus and thus can minimize cabling and greatly reduce the hardware and communication needs for a field deployable health monitoring system. The basic features of the biological nervous system and its application to structures are discussed in the following sections.

2. SENSORY SIGNAL PROCESSING IN NEURAL SYSTEMS

The nervous system enables a living organism to sense the environment and respond appropriately. This system is exceedingly complex, with a large number of components and with an extremely large number of interactions between these components. We will describe briefly the architecture of the neural system, how the system processes information, and how its principles can be applied to SHM. Since our interest is in sensory information, we will focus on how the neural system processes information.

2.1 Structure of Neural Systems

A typical neural system consists of a large number of relatively few types of nerve cells or neurons as shown in Fig. 1(a). For example, a mammalian brain has billions of neurons. Simpler neural systems have fewer neurons as shown in Fig. 1(b), as few as tens to hundreds. All these systems exhibit the ability to process complex information. Neurons are cells that have all the structures common to all living cells: they have a nucleus and other cell organelles, and they are delineated from the environment by a cell membrane. The biological nerve cells, however, are designed for one special function; the rapid processing and transmission of information over long distances. Information transfer in the neurons occurs at the level of the membrane, by means of electrical signals that propagate along the membrane without attenuation. While the mechanism of generation and propagation of this signal (called an action potential) is known, a detailed description of this process is not germane to this discussion. It suffices to note that the neuron is an electrical device with multiple analog inputs (called dendrites) and a digital output (called an axon). Each analog input has the properties that a neuron is stimulated chemically by a variety of neurotransmitters, and these chemicals are released from various cells (including other neurons) that form connections (called synapses) with the neuron. When the neuron is stimulated, the membrane potential changes in a graded manner proportional to the magnitude of the stimulus. Depending on the neurotransmitter, membrane potential can decrease or increase. This digital output has the properties that: (1) the action potential is all-or-none; the size of the action potential is independent of the size of the stimulus, and is not attenuated as it propagates along the axon; (2) the action potential is generated when the membrane potential changes gradually from its resting value (~ -70 mV) and crosses a threshold (~ -50 mV); this results in noise suppression
because small random variations in membrane potentials do not trigger action potentials; (3) the magnitude of the stimulus is indicated by the frequency of action potentials; the greater the stimulus, the greater the number of action potentials generated per second; (4) the region of the membrane that has produced an action potential cannot produce another one for a certain amount of time (called the refractory period); this ensures that the action potential only propagates in one direction, and (5) these properties indicate that information is transmitted by the axon by frequency modulation, resulting in reduced noise in the system. Once an action potential reaches the end of the axon, electrical signals trigger the release of neurotransmitters, and the process repeats at the next neuron.

Figure 1. The biological neural system; (a) generalized neuron model, (b) visual cortex, (c) levels of information processing in man.

2.2 Signal Processing by the Neural System

We can visualize the neural system in terms of levels of organization. The system is arranged hierarchically as shown in Fig. 1(c). At the top is animal behavior, mediated by systems and pathways in the brain; these systems are made up of centers and local circuits, which in turn are made up of neurons. Neuronal activity (action potential) is initiated by microcircuits of synapses. Synapses are actually chemical connections that result in ion channel regulation and local changes in membrane potential. We can also think of the neural system in terms of levels of information processing. It is obvious that the further we move into the system from the input, the higher the level of information processing. Taking the visual system as an example, the retinal ganglion cells respond to the local intensity of light; this is the information that is processed at this level. But at the level of the visual cortex (the area of the brain that deals with stimuli from the eye, Fig. 1(b), cells respond, for example, to oriented bars of light. This information has to do with large areas within the field of vision of the animal. In the primate brain, 25 areas have been identified that predominantly or exclusively process visual information. The information from each area of the retina is fed into all these areas. For the purpose of SHM, we can consider the following properties of a neural system: (1) information proceeds through the system through different levels (hierarchies); (2) information is processed at each level; the level of processing is higher the farther away from the input; (3) information is synthesized at each level, and a decision is made as to what is sent forward to the next level; (4) the system has mechanisms for noise suppression. There is also interconnection between sensory cortices that is not considered now due to the complication.

It is important to consider the geometry and spatial density of the biological nervous system and how information flows through this system. The typical neuron described above has a soma or cell body, the thread-like extensions called dendrites, and a single projection called an axon. The dendrites, which act as the inputs to the neuron, generally look like trees branching into finer and finer structures with the trunks extending from the neuron cell body. The "leaves" of these input trees terminate at synapses (gaps) that receive messages from other neurons. The output of a neuron, called the axon, also looks like a tree (with a long trunk), which may also branch into finer and finer structures. The "leaves" of the output axon tree also terminate at synapses that communicate with the inputs (terminal dendrites) of other neurons. The
A typical neuron receives information from hundreds or thousands of dendritic branches. Each of these inputs reflects either (a) a datum of sensory input, or (b) the judgment of another neuron. Essentially, the neuron waits until the sum of its weighted inputs exceeds its characteristic threshold level, at which point its electrical potential explodes by sending an action potential down its axon. It thus summarizes these hundreds or thousands of analog values into its own judgment, usually expressed as a single bit of information (yes or no). Each layer of neural processing exhibits the ability to extract increasingly abstract levels of information. Key to this process is the concept of feedback, without which a net of neurons would be unable to learn. The relative strength of each synapse may be increased or decreased to better reflect the desired response. There appear to be specific modulatory neurons that facilitate this process. The performance of each neuron is constantly being monitored, and the synaptic strengths are continually readjusted to improve the overall performance of each layer of the network. Neurons can also grow new dendritic and axon branches and create new synapses with other neurons. While the electrochemical implementation of the neural process is complex, the basic computational paradigm is simple and powerful. In essence, a neuron takes the outputs of other neurons, weights each of these values according to a set of changing synaptic weights, takes the sum of these weighted values, and then compares the sum to a threshold value. It then communicates its fundamentally yes or no judgment to other neurons. Periodically, the synaptic weights are adjusted to improve the ability of a net of neurons to perform their intended function. The output of each neuron is, therefore, a very simple summary of its inputs. Through elaborate timed cascades and hierarchies of such simplification functions, concepts are realized and decisions made. The idealization of the structural neural system is based on the simple computational paradigm described and does not require explicit modeling of the electrochemical processes.

3. DESIGN OF A NEURAL SYSTEM FOR STRUCTURES

Human neurobiology is used to develop sensory intelligence in structures by creating artificial systems of neurons with simulated dendrites, axons, and synapses. The generalized neuron is designed to receive many inputs, produce a single output, and have that single output rapidly distributed to one or more other neurons. The neuron dendrite and axon are analogous to an electrical transmission line with a transverse time varying negative resistance element in parallel with a high capacitance. The equations describing the propagation of neuron action potentials derive from the classical equations for wave propagation along electrical transmission lines. The basic mechanisms and architecture responsible for neuron activity can be modeled using neural network analysis and replicated using engineering materials.

Nerve fibers (dendrites) can be designed for sensing waves in structures using piezoceramic fibers and ribbons. The piezoceramic fiber is electroded on the top and bottom surfaces using a photolithography technique and is poled at a high voltage. The fiber then becomes a self-powered sensor that generates electrical charge when strained. The electrical circuit model for the piezoceramic fiber is a capacitor in parallel with a current generator. This is similar to the electrical circuit model of the neuron dendrite and axon membranes, where a capacitor is in parallel with a conductance and voltage source. A conductance and voltage source is similar to a current source. In the neuron, signals stream in from the thousands of branches of its dendrites, each representing a message from another neuron. Some of the messages are subtle while others are urgent. The function of the neuron is to render a judgment. It does this by summarizing the thousands of chaotic messages it receives into a coherent answer. Its conclusion is simple: it either sends its characteristic threshold message or it doesn't. Based on the biological neuron, a unit cell of a neural composite material
A neural composite structure can be constructed by embedding or bonding to the surface unit cells in laminated composite or textile composite structures. Each of these unit cells will have the following features: (1) long piezoceramic tapes whose segments act as independent sensors (dendrites) that detect damage to the structure by measuring AE waves generated by cracks in the material or breakage of fibers (Fig. 2, detail A). The piezoceramic fiber can also potentially measure dynamic strains or "pain" within the structure that is useful for monitoring and regulating load paths within the structure to extend its safe life; (2) an embedded electronic chip termed a "Transducer Bus Interface Module" (TBIM) [21] that conditions the AE signal and performs the data processing. The TBIM itself is made of an analog ASIC (Application Specific Integrated Circuit), for analog signal conditioning, and a digital ASIC which performs the quantification, pattern recognition, timing, and short time data storage, (3) a digital data bus analogous to the cell axon will be the channel of communication between the TBIM’s in the unit cells and the CPU. Further, this bus also powers the TBIM’s. A Transducer Bus Controller (TBC) will be located in the CPU, and (4) the main CPU will assemble the processed information sent by the unit cells, and assess any damage growth that may be occurring in the structure. The CPU is analogous to the brain and gives the structure intelligence. A special feature of this design is that the acoustic emission or dynamic strain data processing takes place within the respective unit cell, and only the processed information is communicated outward through the interface bus. Further, the fibers are connected to tailor the sensitivity of the unit cell and match the environmental conditions under which the structure is operating. The charge output from the sensor elements flows to the TBIM, which is analogous to the cell body or soma). The bi-directional communication between the unit cells and the CPU takes place over the single digital data bus, thus eliminating most of the cumbersome cables.

The operation of this synthetic multifunctional material will be as follows: In the beginning, the CPU will initialize all unit cells, including their short-term clocks. The CPU then will query each unit cell at time intervals of the order of a few tens of seconds to download the gathered information. The TBIMs in the unit cells will perform the digitization and analysis of the AE signals and store only those processed data that are recognized as related to damage growth in a tabular form within its memory for uploading to the CPU. The parameters that will be stored in the TBIM’s will include parameters such as the time of occurrence of the AE event, energy content of the AE event, amplitude, duration, and the pattern of the AE signal envelope. The TBC addresses each TBIM sequentially, to upload the processed information from the TBIM's which is permanently stored in CPU. The data bus is analogous to the axon, and the TBC/CPU are analogous to the intelligence or brain in the hierarchy of the biological system. The ASIC’s themselves will have the ability to be reprogrammed by the CPU so as to optimize the AE data acquisition and analysis. This is similar to how the synapses are modified to improve the sensitivity of the neuron to specific stimuli. The digital bus is used to greatly reduce the effects of electrical noise and interference in the circuitry. This is similar to the digital output of the axon, which reduces noise. Details of the expected operation of the TBIM and AE sensors are given in the following sections. The TBIM, TBC, and the interface bus will be designed and non-miniaturized prototypes of these modules will be fabricated for later experiments. Presently, the operation of the TBIM and TBC are being modeled using a PC.

AFC materials using PZT fibers or ribbons [22-24], or PZT wafers can be used to construct long continuous dendrites or sensors. Interdigitated (IDT) electrodes are put on segments of the fibers and used to pole and electrically connect the sensor nodes. The nodes can be connected in series to reduce the capacitance and the time constant of the circuit, but the resistance of the circuit must be kept low. This is similar to putting more capacitors in series with the membrane capacitance in the cell [25]. This is called myelin, and myelinated nerves contain the fastest conducting axons in the nervous system. The AFC is thermally stable, there is great flexibility in tailoring and designing a sensor material, and it is strong and rugged enough to be used on helicopters, armor, and in a layered composite. The piezoceramic ribbons in a soft matrix produces a sensor material that is more crack resistant and has higher ultimate strain than monolithic ceramics. The use of fibers/ribbons retains most of the stiffness of monolithic piezoceramic patches, and the unidirectional alignment creates the desired sensing/actuation in a single direction. The structural and AFC properties are used in wave propagation simulations to determine the dynamic response of the sensor composite. Some results from approximate simulations are included in a later section of this paper. The size, shape, and distribution of the individual sensing elements in the neural sensor network, and the electrode patterns can be optimized to obtain (i) a high fidelity reproduction of the stress wave signals (ii) a clear separation of packets of wave forms from individual sensor elements, and (iii) to provide the greatest sensitivity to the most critical areas covered by the unit cell. The electrode configuration can be designed to pole the fibers axially, or through their thickness. Thin foil conductors (IDT electrodes) perpendicular to the fibers will be used on the top and bottom of the fibers. The conductors are used both for electroding and poled poling. The advantages of these designs are: (a) if the sensor is poled through the thickness the electrodes are easy to manufacture, (b) non-conductive structural fibers can be mixed with the sensor fibers, or conductive fibers can be put in adjoining layers, (c) the sensor can measure dynamic strains above 0.5 Hz., (d) the sensor can be one cell of the neural system and AE’s can be detected from all segments simultaneously, and (e) ribbons can be used instead of fibers which makes electroding easier, the polarization is more uniform, and the ribbons are larger than fibers and easier to fabricate. The
electrodes are used for poling the sensor material. Figure 2 gives a schematic of a Neural Composite Material built using AFC nerves. The nerves are modeled as a continuous sensor with a plurality of nodes. The Transducer Bus Interface Module (TBIM) is an external replaceable and upgradeable data processor that is addressable by a Transducer Bus Controller (TBC) and a PC.

4. STRUCTURAL INTELLIGENCE

The structural intelligence of the neural composite material will reside in: (a) the TBIM, which performs local processing of AE signal; (b) the TBC that controls the digital interface bus; and (c) the CPU where the processed information from the unit cells is integrated to assess and monitor the structural health. The TBIM, the TBC, and the digital interface bus will be designed based on work done for pressure sensing [21]. The TBIM module will be fabricated at the pre-miniaturization level to establish the feasibility of the embeddable TBIM processor system. The preliminary design for the electronics needed to interface the piezoceramic sensor fibers used in the neural material will include signal conditioning, data processing, and network communications. The signal from each unit cell will be digitized at a high sample rate (up to 1 Msamples per second) and signal processing algorithms will be applied. The desire is to locate the TBIM’s with the analog signal conditioners as close to the distributed sensor as possible. The network bus will be based on a smart sensor bus [21]. The TBC will have the ability to convert from the transducer bus to an Ethernet bus, providing a convenient means of interface to the transducer bus using a personal computer with an Ethernet card. Using the personal computer, the user will be able to configure individual TBIMs on the network, as well as display and store information. The system will condition the signals from the distributed sensors and provide the needed processing, communication and user interface capabilities. This work will establish the feasibility of miniaturizing the TBIM’s and minimizing power consumption. The Transducer-Bus-Interface-Module (TBIM) will provide: (1) analog signal conditioning to the piezo-ceramic sensor; (2) high speed analog to digital (A/D) conversion (up to 1Msps); (3) data storage; (4) digital signal processing; and (5) digital bi-directional network communications to a Transducer-Bus-Controller (TBC). Some of the signal processing (such as envelope detection) may be accomplished in the analog domain to lower sampling rate requirements. The TBIM provides the ability to network sensors, thus eliminating point-
to-point cabling. Data will be transmitted over the network in non-real time after the signal has been captured in memory. A TBC is required to act as the “master” of the sensor bus. TBIMs are “slaves” in the sensor bus. Figure 3 shows the interconnection of TBIMs, a TBC, and a host computer used to display the data.

![Figure 3. TBIM Block Diagram, and sensors - TBIMs - TBC - Computer Interconnection (figure courtesy of Endevco Corporation).](image)

4.1 Training the Distributed Sensor Network

The architecture of the network consists of multiple long piezoelectric sensor fibers that are segmented and connected to TBIM’s. The TBIM’s are connected through the axon or data bus to the TBC and then to the central processor unit (CPU) or brain which is the PC with neural network software. Whenever there is AE activity, TBIM’s acquire and process the AE data to provide a set of parameters that may include the amplitude, energy, shape, and time of arrival of the signals. Conventional AE techniques use a number of procedures for characterizing and quantifying AE data, and these procedures will be examined for use in the distributed sensors. In addition, new algorithms will have to be developed to quantify the waveforms from the distributed sensors.

The operation of this neural material will be as follows: In the beginning, the CPU will initialize all the unit cells, including their short term clocks and query each unit cell at time intervals of the order of few tens of seconds to download the gathered information. The TBIMS in the unit cells will perform the digitization and analysis of the AE signals and store only those processed data that are recognized as related to damage growth in a tabular form within its memory for uploading to the CPU. The parameters that will be stored in the TBIM’s will include the time of occurrence of the AE event, energy content of the AE event, amplitude, duration, and the pattern of the AE signal envelope. The TBC addresses each TBIM sequentially, to upload the processed information from the TBIM's which is permanently stored in CPU. We present here a strategy for training the sensor network:

(a) To begin with the CPU initializes all the unit cells – resets the local clocks, clears the memory, and sets the threshold levels, so that the unit cells are ready to receive AE signals, and process the data.

(b) After initialization, the CPU periodically queries each TBIM for AE activity and if such activity was present it receives the processed AE parameters. If the value of parameters such as signal energy cross a certain threshold, or if parameters such as signal shape deviate from preset (or learned) values, then; (c) the CPU integrates the information from all the TBIM’s to assess the damage level; (d) based on programmed values, the CPU determines the structure’s condition to be (i) normal, (ii) a drift or variation in the structural response parameters attributable to operating condition but not indicative of damage, (iii) small damage, or (iv) large damage and impending failure.

1. IF structure’s condition is (i) listed above, THEN the CPU does not send any signals back to the TBIM’s.
2. IF structure’s condition is (ii) THEN the CPU sends signals back to the TBIM's to adjust within limits current values of the parameters to be the new threshold to increase sensitivity to the signals it is receiving; further, the CPU will change its own sensor network parameters to reflect the drift; the CPU will also signal the user about a variation occurring in the structural parameters and using the neural network will try to relate this change to temperature, load, contamination, or other reasons;
3. IF structure’s condition is (iii) THEN the CPU will record the time, location, type and severity of the damage or overload; the CPU will log a record of the damage state at that location; and the CPU will also signal the user about occurring structural damage or overload; the CPU will survey the strain history over the structure and make a recommendation on how to change the operating condition to alleviate or redistribute the load to prevent the initiation or propagation of damage;
4. IF structure’s condition is (iv) the CPU sends a signal warning the user of impending structural failure; the CPU makes a recommendation to the operator to immediately change the operating condition to avert failure.

In order to train the sensor network, a procedure of calibrating each unit cell should also be established. Although the different unit cells attached to structure may be similar, the dynamics and wave propagation characteristics may vary from point to point on the structure. These differences can introduce errors in the quantification of the AE activity, unless the each TBIM takes these differences into account in reducing the data. The calibration procedure would establish the
threshold levels, data acquisition time window, and other related parameters. A final point to note is that the software in the CPU will be robust enough to identify the failure of a sensor or TBIM; redundancy will be built into the sensor network, such that most damages will be detected by more than one unit cell.

5. MODELING AND SIMULATION

The neural sensor is investigated analytically considering passive sensing of acoustic emissions and also stress wave propagation to detect damage. With continuous sensors, we can have many interconnected sensors, and use only one channel of data acquisition. This is because the sensor can be distributed throughout the structure and hence be close to any AE site. This will allow the AE signal to be detected before it decays or is modified by the structure’s dynamic characteristics. The polarization, electrode patterns, and segment connectivity are important design factors that must be optimized in designing sensors to detect AE’s. Interdigital electrodes are used to pole and electrically connect to the sensor. The modeling performed to study continuous sensors couples the elastic equations of a plate structure to the piezoelectric constitutive equations. An elastic model of a plate is used to simulate the response of the sensor to an impulse generated by a PZT patch at the center bottom of the panel. A step voltage is applied to a PZT patch located at the middle of a plate to generate the acoustic wave. The segments \( s_1, s_2, \ldots, s_n \) model the interdigitated electrodes over certain lengths of the AFC. Since the AFC is poled using the interdigital electrodes, each segment acts as a separate sensor, with all sensors connected together. The segments can be spaced appropriately and connected with alternating polarities to detect a desired frequency of structural vibration. The simply supported plate is modeled to study the benefits of an AFC sensor for measuring strain and acoustic emissions. The average strains over the area of the sensor are used to compute the voltage output from the sensor. The voltage output is computed from based on the piezoelectric constitutive equations and the thickness and the capacitance of the sensor. For a simple approximation to model a unidirectional AFC on a plate, the open circuit voltage \( V_0 \) can be approximated assuming the current flow is zero and using the average strain over the sensor nodes as:

\[
V_0 = -eA_s \bar{\sigma} / C_p + V_{IC}
\]  

(1)

where \( V_{IC} \), \( e \), \( A_s \), \( C_p \), \( \bar{\sigma} \) are the initial voltage across the sensor, and the induced stress constant, electrode area, total capacitance, and average strain of the sensor, respectively. The open circuit voltage calculation neglects the internal resistance of the piezoceramic material that will discharge the capacitor slowly and prevent measurement of signals that are at very low frequency. The electric circuit model of the series sensor is shown in Figure 4. In Figure 4, \( i_c \) represents the component of the current going through the capacitor of the model, and \( i_p \) represents the component of the current generated by the piezoelectric fibers.

Figure 4. Electrical model of connected AFC sensors.

In the simulation, the elastic solution is computed at small time steps, and eqn. (1) is used to compute the voltage. The solution approach presented requires that the rate of change of the excitation is less than the speed of propagation of waves in the material. Using this solution, continuous sensor designs can be practically studied to sense AE signatures and wave propagation. The simulation is performed for a composite fiberglass plate with an integrated AFC tape sensor shown in Fig. 5(a). The AFC sensor strip is called a unit cell. An impulse load is applied at the center of the plate. The composite plate is 1.02mx1.02mx8mm (40x40x0.316 in) in size. The elastic modulus \( E \) for the plate is 22.063GPa, the weight density of the fiberglass plate \( \rho \) is 16015 N/m³, and the damping ratio \( \xi \) for all vibration modes is 0.05. The voltage response of the sensor in Fig. 5(b) shows a voltage peak on the order of 1 volt indicating that the sensor can detect strains on the micro-strain level if the resistance of the circuit is low. Figure 5(b) shows the voltage output from the square neural sensor due to the pattern of wave propagation shown in Figure 5(c). The plate displacement due to wave propagation is shown at the times 20, 100 and 300 micro-seconds. Sixteen sensor nodes are used to form the neural
composite material. There is only one output signal from the neural sensor. This model is used to optimize the configuration of the neural system including the size of the nodes, the fiber direction, and the shape of the nerves. Comparing the time response in Figure 5(b) with the wave response in Figure 5(c), we see that at 20 microseconds the wave has not reached the sensor and the voltage is zero. At 100 microseconds, about two and one half waves have passed over the sensor and the voltage is about -0.6 volt. After about 250 microseconds, lower frequency waves with longer wavelengths begin passing over the sensor and waves reflecting from the edges of the panel are combining with the incident waves. Damping in the model causes the wave amplitudes to decay as time increases. This wave behavior will be verified by experimentation.

Figure 5. Simulation of a neural composite material; (a) the neural system on a composite panel, (b) the time response of the neural system due to an impulse from a PZT patch in the center of the panel, and (c) wave propagation in the panel.
6. EXPERIMENTATION USING CONTINUOUS SENSORS

Experiments are being performed to verify the characteristics and potential of the sensor system. However, since AFC sensors are currently expensive, standard discrete 1.27cmx0.95cmx0.25mm PZT sensors [26] are used in this experiment in order to present the concept of continuous sensors. The small size of the PZT's will allow higher frequency components of acoustic waves to be measured. The PZT patches sense strain in any direction in the plane of the plate. All of the PZT sensors are connected serially to form one continuous sensor with only one channel of data acquisition to a digital oscilloscope. Pencil lead breaks using a 0.5mm lead are used to simulate AE. The data is collected through a single channel to a digital oscilloscope and then downloaded on a laptop for plotting. The experiment is performed using a 0.91mx1.2mx6.3mm fiberglass panel (Fig. 6) with the continuous sensor. The voltage response due to a lead break on the panel is shown in Figure 7. The top and bottom traces correspond to the single sensor and the continuous sensor, respectively. The AE signals from the single node sensor and the continuous sensor are nearly the same when the AE source is near a node of both at location A. When the AE source is far away from the single node sensor as shown in AE location C, the high frequency part of the AE is nearly missing in the response of the single sensor while the continuous sensor is able to capture the leading edge of the signal. Capturing the leading edge is crucial to identify the source mechanism [27-32] because the later part of the signal is dominated by the structural characteristics and may resemble ambient vibration and noise that likely is present in the structure. In this case, the continuous sensor is superior for AE detection compared to the single sensor. Continuous sensors are particularly advantageous for monitoring attenuative materials such as carbon epoxy or glass epoxy composites. The continuous sensor registered a larger amplitude signal and a larger acoustic emission energy, as measured by a commercial AE monitoring system. The continuous sensor can detect and locate damage within the coverage area of the sensor, but cannot exactly locate the AE source due to the continuous nature of the sensor. The maximum number of nodes possible to use in a continuous sensor depends on the resistance and shielding. The experiment with the composite panel showed that the energy levels from AE captured by the continuous sensor are considerably higher than for the single sensor. This is because damping causes much higher attenuation in composites and high frequency data is lost when the AE source is away from the sensor. Preliminary simulations and experiments on a bar indicate that for certain conditions it is feasible to locate the AE sources using a single channel distributed sensor, and this approach is being extended to 2-D damage location. The Fourier Transforms of the response of the continuous sensor and the single node sensor for the lead break at locations A and C were computed (not shown). In these graphs, the amplitude of the response of the continuous sensor was much greater than for the single sensor.

![Image](image_url)

Figure 6. Fiberglass panel with a continuous sensor and the location of lead breaks.

An analysis is performed next to show how the continuous sensor detects AE waves. Consider a continuous sensor with N nodes connected in series. Let the response from the continuous sensor be \( z(t) \), and the response from each individual node be \( x_i(t) \). Then:

\[
 z(t) = \sum_{i=1}^{N} x_i(t) 
\]  

(2)

Now take the Fourier Transform of the sensor response:
\[ Z(f) = \int \sum_{i=1}^{N} x_i(t)e^{-j2\pi ft} dt = \sum_{i=1}^{N} X_i(f) \]  

(3)

The magnitude of the response of the continuous sensor in the frequency domain is:

\[ |Z(f)| = \left[ \sum_{i=1}^{N} X_i(f) \sum_{j=1}^{N} X_j(f) \right]^{1/2} \]

(4)

where * denotes complex conjugate. Letting \( X_i(f) = a_i(f) + \sqrt{-1}b_i(f) \), and substituting this into (16) gives:

\[ |Z(f)| = \left[ \sum_{i=1}^{N} \sum_{j=1}^{N} (a_i(f)a_j(f) + b_i(f)b_j(f)) \right]^{1/2} \]

(5)

Equation (6) shows that at each frequency the magnitude of the response of the continuous sensor is equal to the magnitude of the sum of all combinations of the products of the responses from all the sensor nodes. This means that if all nodes respond at a particular frequency, the response of the sensor will depend on the magnitudes and signs of the individual responses. Most important, however, is that the total response contains the frequency content of all the responses, no new frequencies are added, and no frequencies are removed. When an AE from a crack in the structure in the 100’s of KHz frequency range is picked up by one sensor node that is in the neighborhood of the crack, this response will pass through the sensor and occur in the sensor output unaffected by the lower frequency ambient vibration, and the high frequency of the response will indicate the damage.

Figure 7. Voltage response due to lead breaks on a fiberglass panel. The top curve is for the single PZT sensor, the bottom curve is for the continuous sensor with nine PZT nodes.

6. CONCLUSIONS

The concept of a neural system for structural health monitoring was explored. The main advantage provided by the neural sensor is the ability to monitor large regions of the structure with a small number of channels of instrumentation. Because of this advantage, it is potentially possible to use AE monitoring in those applications for which the acoustic emission technique was earlier found impractical simply because too many channels of AE instrumentation were required. For the continuous sensor with the nodes connected in series there is no degradation in the signal amplitude.

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