Application Specific Instrumentation (ASIN): A Bio-inspired Paradigm to Instrumentation by fusing sensors and AI (SensAI)

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ABSTRACT

Nature has, consistently, been an inspiration for scientists and engineers. In this paper, I present a novel paradigm to instrumentation where we co-develop the sensor and machine learning algorithms to bolster the sensor. This is what happens in most species of animals through generations of coevolution. Such sensor and AI (SensAI) empowered instruments are expected to be inexpensive as well as more efficient (in the applications for which they have been developed). In addition to presenting the modus operandi of this application specific instrumentation (ASIN) paradigm this paper shall also, briefly, discuss some of the successful demonstrations of the ASIN paradigm.

KEYWORDS

Bio-inspired, Bio-inspired Architecture, Machine Learning, Artificial Intelligence, Sensors, Instrumentation

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1 INTRODUCTION: LOOKING AT NEUROETHOLOGY

Conventional instrumentation systems have always aimed for higher sophistication to perform better. So the traditional instrumentation system will measure signals using high resolution sensors. This is followed by steps to extract information from the signal which then are interpreted based on the requirements. Finally, some action is taken based on the interpretation. The inherent philosophy in this has been the separation between sensor system and the decision-making system. In other words sensor systems are designed to be *generic*. The processing chain is further illustrated in Figure 1. Mark that all the blocks after the *Sensor* block can have human intervention and feedback. And the dashed link between the *Decision* and *Sensor* is advocated by most of the intelligent instrumentation work. The work on intelligent and smart instruments [4, 26] roughly follows the same chain of action with an added path for feedback from the decision making block to sensor block.

However, most living organisms follow a different approach in which they have evolved as a system for a very specific task. Due to this co-evolution, sensors and sensory data processing hardware work as a single entity. Many studies into neuroethology have validated this. Animals co-evolve with many other living organisms in their niche ecosystem to develop these sophisticated sensing systems which work very successfully in their niche ecosystem[8, 11, 24]. We shall discuss two neurothological case-studies here.

1.1 How do bats do it?

An example of such co-evolution is shown in Figure 2 taken from reference [32]. In this interesting figure, the scattered return of the sound waves generated by a type of pollen-feeding bat from different types of flowers (of the same species) are shown. As can be observed, the return is high (over a very wide angle of incidence) only if the flower is in full bloom and has real nectar in it! So, the sound wave generated by the bats has been fine-tuned over generations, so that the current generation can well be termed as information sensing processors. There are three major observations from this and other studies done on bats [1]. First of all, the sensing system has evolved for a very particular function. Secondly, there are multiple sensors that the bat uses during foraging. And none of these sensors are of high *resolution* in the traditional meaning of the word. Lastly, bats brain is very simple and mostly works as a correlation processor [33]. It can also be noted here that extensive research on the working of visual cortex [18] have also given similar conclusions. In other words, even in evolved mammals like the human brain does not process the sensory output as it is. Rather it always works in a goal-driven manner, using layers of neurons in the prefrontal cortex [9] to perform certain predefined tasks.

1.2 How do weakly electrical fishes do it?

Weakly electric fishes are simple creatures with some sophisticated abilities. These fishes, mostly found in deep rivers (with very little light), use electricity for three major functions; viz. passive electro-location (by sensing the electric signal emitted by almost all other animals around); active electro-location (by sensing the reflection of electric signal generated by their electric organ discharge (EOD)); and electro-communication (with different members of their species). The sensory cells responsible for electro-communication

[1]The choice of bat is because of two reasons. First of all, because of its unique ability to use sound for visualizing its environment, there has been a lot of study on bat's sensors and brain. Secondly, being a small mammal these studies have been quite confirmatory in terms of how its brain works.

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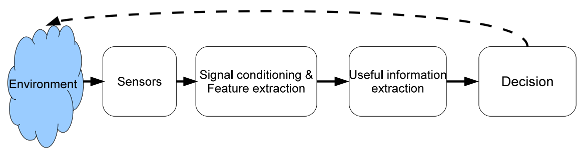

Figure 1: Chain of action blocks in conventional instrumentation systems

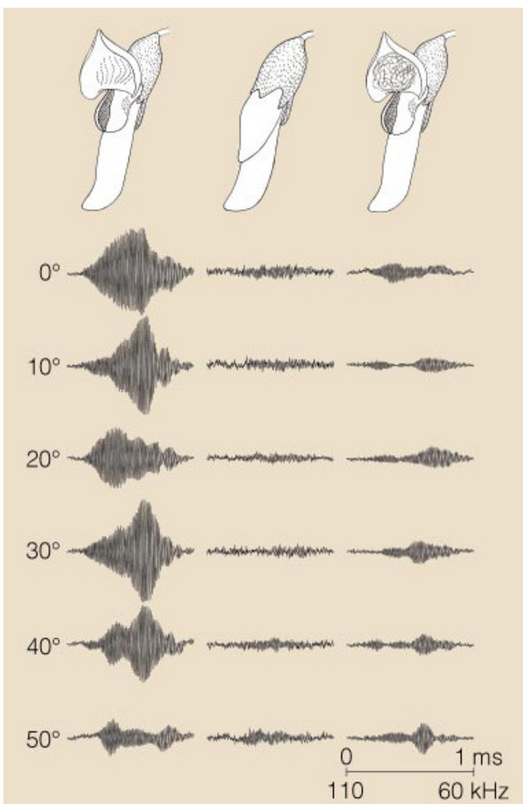

Figure 2: Pollen seeking bats' transmitted waves have evolved over generations to make them a rough information sensing system [32].

(Knollenorgans Electroreceptors) are phase receptors and respond to transients [1].

The receptors end in the electrosensory lateral line lobe (ELL). Something interesting starts happening now. Each electroreceptor trifurcates to three ELL maps: the centromedial (CMS), centrolateral (CLS) and lateral (LS) segments. These three are of different sizes (with CMS being the biggest and LS being the smallest map (In terms of neurone assigned)). They also process the signal for different features so that different behaviours are mapped to different types of burst characteristics. Another interesting phenomena is the fact that the frequency response of the CLS cells changes as per the context (e.g. communication or foraging). This multiple parallel mapping of information is very similar to the way most convolutional neural network (CNN) work. The big difference, however, lies in the way these layers are tuneable depending on the context for the fish.

The ELL signal are next mapped to torus semicircularis (TS) where the information is further organised to many more layers (around 12) and more than 50 neurone types. The exact working of these layers are not very well understood. However, recent studies do show that these are linked with very fine feature extraction.

Information from TS goes to tectum (which is equivalent to the visual cortex of mammals). Both tectum and TS feed information to pallium (which is similar to cortex of mammals). Pallium can, in turn, affect the way TS and tectum map sensory information. The detailed block diagram is given in Figure**??**, taken from [13].

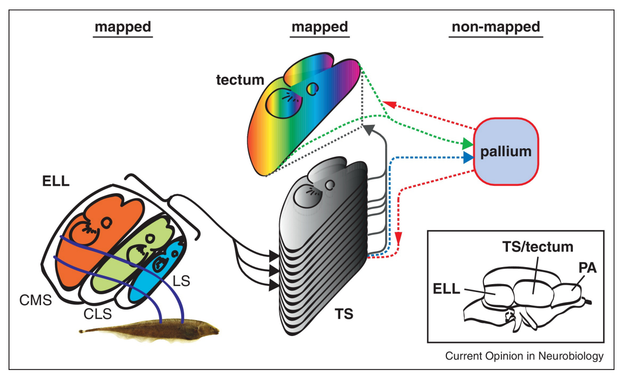

Figure 3: Mapping of sensory information in weakly electric fish [13].

A WEF, like many animals, can achieve a range of marvellous tasks.

(1) **Coding based sensor tuning:** Depending on its situation and motif the fish has the ability to tune what information is collected and represented at the sensors. This is changed by deciding what coding scheme shall be used by the sensors in the skin to send across to ELL [23]. This is an elegant way to fuse symbolic and non-symbolic layers in modern AI. It is not the best solution (as its not very generic). However, it can be the starting point.
(2) **Hyper-acuity:** Many animals can resolve events at a scale which is finer than what their sensors can achieve. The WEF's neurological study seems to suggest that this is achieved in the fish by the use of multiple spatial representation of the

information coming from the sensors. And the burst characteristics in these maps represent various events [23, 25]. Hence it seems the ability of apparently higher resolution of detecting "certain events" comes from blowing up the information into a spatial map and inferring from these maps.

(3) **Ambiguity of information from a single neuron:** Multiple spatial neural maps are the way to handle and extract information. A single neuron will be part of multiple such mappings. Hence, the exact information represented by a single neuron is ambiguous. This helps in making the whole system more robust and less dependent on local blocks.

We discussed the working bats and the WEFs. In both these animals sensors and processing architectures have evolved to create application specific instruments which can achieve high fidelity decision-making using non-sophisticated sensors and processing. From these observations, we have worked on a new design of instrumentation, which we call application specific instrumentation (ASIN).

In rest of the paper I shall present the configuration of a generic ASIN system in Section 2. In Section III a new framework for resolution shall be developed. Section IV will present some applications using ASIN. Lastly I shall conclude in the last section.

2 ASIN CONFIGURATION

The configuration of the proposed instrumentation is shown in Figure 4. In the following, we describe the major components of ASIN system and how they work.

- *Sensors:* The sensors are the interface of ASIN to the environment. There are two major ways in which this is different from the sensor block of Figure 1. First of all, each individual sensor in ASIN is of low or crude resolution. Secondly, each sensor interacts with the environment through a preselected application specific measurement matrix. Usually, if e is the environment parameter to be sensed, a sensor measures s through a measurement process P. I.e.

$$s = Pe$$

A high resolution sensor is one which measures e as truthfully as possible, and hence for an ideal sensor P should be as close to an identity matrix as possible. The basic sensor is fine-tuned in ASIN with application specific measurement matrix, P_{ASIN}. Hence, the final measurement is s', where

$$s' = P_{ASIN}Pe.$$

The design of a suitable application specific measurement matrix is one of the major tasks for ASIN design. This needs focusing the end-goal to as few decisions as possible and to try to make these decisions binary (to make the whole system simple).

- *Correlator Processor:* Given that the sensors have been designed with some intelligence, the next step is a simple correlation type processor, instead of a high performance processor (which usually handles signal processing and information extraction).
- *Interpreter:* The final block is Interpreter which interprets the output from the correlation processor and gives a final decision level. And as we discussed before, the final decision need to be as few as possible and preferably with a binary value.

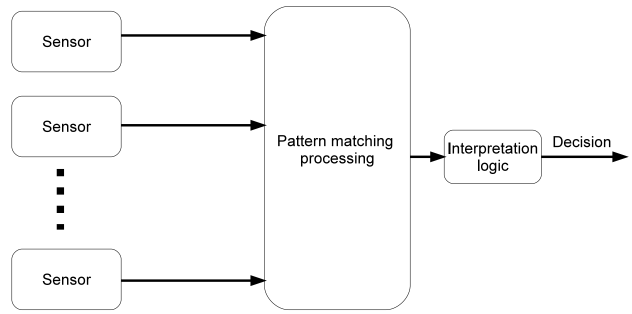

Figure 4: Block diagram of the basic ASIN instrument.

3 REDEFINING RESOLUTION

One of the major figures of merit of any instrumentation system is its resolution. As per the Measurement Systems Analysis Manual " the resolution of an instrument is δ if there is an equal probability that the indicated value of any artifact, which differs from a reference standard by less than δ, will be the same as the indicated value of the reference". There are few ways in which we will refine this definition to create a new definition of resolution for ASIN. Depending on that we shall define two different types of resolutions.

3.1 Neyman-Pearson Principle based Definition

For a generic instrument, as it says in the definition of the resolution, they measure the "value of any artifact". In the context of ASIN this becomes the "value of any artifact of interest". Secondly the way we measure this artifact using ASIN is by using pattern recognition algorithms. Hence the output from ASIN is mostly a propbability, P_p that a certain "artifact of interest" is present. Let us represent the artifact of interest as θ. For a given task there will always be cases of misclassification which will create events of false alarm giving a probability of false present, P_{fp}. Then using Neyman-Pearson principle the goal of desinging an ASIN is to maximize P_p for a given P_{fp}.

Definition I: The Neyman-Pearson principle based resolution (δ_{NP}) can be defined as the maximum change in the artifact of interest, $\Delta\theta$, which for a given ASIN makes sure that the change in the probability of false present $\Delta P_{fp} \leq$ an arbitrary small number ϵ.

3.2 Cramer-Rao Bound based Definition

From a data-centric point of view for an "artifact of interest", θ, we use ASIN system to capture some signal ζ. One of the major empowering concept of ASIN is the hypothesis that we can estimate θ from ζ even when the exact phenomenological link from θ to ζ is not well-modeled. This way of putting the ASIN operation helps in looking at the problem from a parameter-estimation point of view. And in parameter estimation one of the important figures of merit is Cramer-Rao lower bound (CRLB) which is the lowest variance in the estimate. CRLB is the inverse of Fisher information[2]

$$I(\theta) = E\left[\left(\frac{\partial l(\zeta;\theta)}{\partial \theta}\right)^2\right]$$

, where $l(\zeta;\theta)$ is the natural logarithm of the likelihood function and E represents the expectation operation. For ill-defined mapping like what we deal with in ASIN Fisher information can be found numerically as well [31].

Definition II: The Cramer-Rao principle based resolution (δ_{CR}) can be defined as the maximum change in the artifact of interest, $\Delta\theta$, which for a given ASIN makes sure that the change in the Fisher information $\Delta I(\theta) \leq$ an arbitrary small number ϵ.

4 SOME APPLICATIONS

In this section, we describe two simulation based validation of a limited version of the ASIN system we discussed in the last section. The limitation of the version of ASIN used lies in the fact that the sensors used in this setup are generic instead of being customized for the final goal.

4.1 Target specific waveform

As we discussed in Section 1.1, bats have co-evolved with other species to have highly specific waveform fine-tuned to their task. This results in a higher return amplitude of the scattered signal when the target is the one for which the wave has been designed for. This methodology of outsourcing sensor intelligence to the sensing signal itself makes the sensor signal processing algorithms extremely simple. Just threshold based detection can directly recognize the target. Inspired by this, we tried to develop methods in radar signal processing where the radar signal is designed for different targets[14–16]. This resulted in much simple algorithms for target recognition.

4.2 ASIN based breast tumor detection

In the first demonstration we use UWB based Radar to measure breast tumor. This is an active area of research [7, 10]. But most of the work in this domain follow the conventional instrumentation path as elucidated in Figure 1. The main focus is on the development of a generic instrument of high resolution. In the ASIN based approach, we fix the end goal first. We fixed the final goal to be the detection of the presence of tumor in breast. For this instead of generating a 3D image of the breast tissues, which requires the use of a UWB Radar array, we used just one UWB sensor node. The correlation processor block of Figure 4 was simulated using a single layer neural network, which was first trained with few training measurements (all using single UWB sensor). The final system was able to detect tumor with an accuracy of 98% even in the presence of tissue bundles whose relative permitivity was much higher than that of normal tissue. Further details of the work can be found in [19].

[2]As we are discussing about resolution with respect to any given artifact of interest we will only deal with scalar θ.

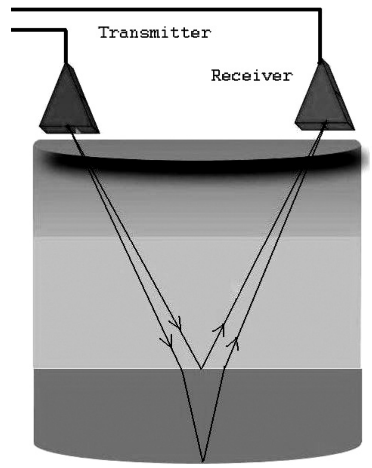

Figure 5: Setup for measuring sludge volume in oil tanks using a single UWB Radar sensor.

4.3 ASIN based sludge volume estimation

In a second attempt to implement an ASIN type system, we tried to build an instrument using UWB Radar to measure sludge volume in oil tanks. The experimental setup is shown in Figure 5. Again, the conventional approach is to use an array of UWB transceiver sensor nodes to first form a 3D image of the tank bottom, and finally to use image processing steps to estimate the volume of sludge. In the ASIN based approach, we first trained the correlator processor, again implemented by a single layer neural network. In the testing phase, we changed the volume of sludge in incremental steps and for each volume we also changed the sludge profile. The performance of the system is best represented by a regression coefficient, between the actual volume and the estimated volume. We got a regression value of 0.91 using simulation based experiments, and of 0.88 using practical measurements.

4.4 ASIN based Fake-medicine Detection

Counterfeit medicines have become one of the world's fastest growing industries, becoming a global pandemic as it jeopardizes patient health and recovery. It has been reported that the use of counterfeit drugs has been linked to an increase in morbidity, drug resistance, and in the most severe cases, death [5]. A similar problem is that of pesticide residue ingested from fruit and vegetables which has been linked to an increase in cancer, as well as negative effects on the reproductive, immune and nervous systems [17] [12]. Spectroscopy and chromatography methods are often used to test for contaminants. However, they are expensive and complicated to use. There is a need for an inexpensive and easy-to-use technological solution to detect counterfeit medicines or contaminated food. If we analyze this problem from the end-user's point of view then it usually is a YES-NO question the user is interested in. For example, a healthcare worker in a remote village would just want to know if a given medicine sample is the medicine it says on the cover or not. This problem statement aligns nicely with the ASIN's description.

We have worked on an ASIN-based solution for this[22]. We developed a visible spectroscopy based counterfeit medicine detector using machine learning. This technique allows reliable predictions to be made without requiring the necessary knowledge of pharmaceutics. The device was proposed as a solution to combat medication adulteration. The system was also used for the detection of lethal doses of pesticide residue in fruit juice which poses a threat in nearly 70% of all commercial fruit sold [6]. The spectrometer diffracts the continuous spectrum produced by an incandescent light-bulb throughout the visible region of the electromagnetic spectrum, $390 - 700nm$. The incident light travels through the entrance slit where it is then scattered by the sample of interest. Finally the scattered light is diffracted by the DVD diffraction grating in order to produce a continuous visible spectrum which is then captured by the CMOS detector, a logitech C170 webcam. In lab-conditions, we achieved remarkable accuracies of up to 100% thus proving that the concept is not only possible but feasible. The interested readers are requested to refer [22] for further details.

4.5 ASIN based CommSense

The effort to use existing communication systems as radars and vice versa has been there since the last great war. One of the ways we can exploit communication signal to know about the immediate environment is by exploiting the pilot signal. Pilot signals are used to estimate channel noise. This information is used in channel equalization in the receivers. Changes in the pilot signal are not fine enough to detect individual targets. However, they can be used to identify changes in the environment. If we know the kind of changes we are looking for then we can use machine learning to identify the "events of interest" from the changes incurred by the pilot signals. This way to sense, invented by the author, was named communication based sensing or CommSense[20, 21]. Over the last five years we have demonstrated its feasibility using both GSM[2] and LTE[28] communication signals and its application in various domains[3, 27, 29, 30].

5 CONCLUSION

In nature, most animals co-evolve their sensors in their ecosystem for very specific problems. Inspired by this, in this paper a new way to instrumentation was presented named application specific instrumentation (ASIN). This way of co-designing sensors and AI (SensAI) algorithms for a specific problem is inspired by neuroethology. This is a biologically inspired scheme, where the focus is on designing instruments for very focused problems, so focused that the decision can be made binary. The proposed scheme is expected to be less costly, require much less computational overhead and to perform better for specialized applications. We have also discussed a few pieces of work where we have developed interesting innovations and solutions based on ASIN design-principle. It is expected that more solutions would emerge in the future where sensors and machine learning algorithms are jointly developed for highly specialized applications.

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