minedICE: A Knowledge Discovery Platform for Neurophysiological Artificial Intelligence

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Abstract. In this paper we present the minedICE^{TM} computer architecture and network comprised of neurological instruments and artificial intelligence (AI) agents. It's called *minedICE* because data that is "*mined*" via **I**ntra**C**ortical **E**lectroencephalography (*ICE*) located deep inside the human brain procures (*mined*) knowledge to a Decision Support System (DSS) that is read by a neurosurgeon located either at the bedside of the patient or at a geospatially remote location. The DSS system 1) alerts the neurosurgeon when a severe neurological event is occurring in the patient and 2) identifies the severe neurological event. The neurosurgeon may choose to provide feedback to the AI agent which controls the confidence level of the association rules and thereby teaches the learning component of minedICE.

1 Introduction

The detection and interpretation of abnormal brain electrical activity in patients with acute neurological injury remains an area of significant opportunity for technological advancement. Neurosurgeons know that when a patient arrives in the emergency room (ER) with a severe head injury, they rely on their intuition and relatively limited external data to choose the necessary treatment modality. Aside from the initial injury, the brain tissue in these patients is extremely susceptible to secondary injury from ongoing abnormal (and preventable) physiological processes. Although a number of invasive neuromonitoring systems exist, current modalities either provide indirect measurement of brain health (and are therefore difficult to interpret) or have limited sensitivity and specificity for accurately identifying critical and deleterious changes in brain health. To overcome this limitation, Waziri developed Intracortical Electroencephalography (ICE) [10] a technique by which specialized multicontact electrodes can be placed into the cerebral cortex through a burrhole generated at the bedside, as illustrated in Figure 1. Through the use of ICE, high amplitude and high fidelity EEG data can be recorded in an otherwise electrically noisy environment.

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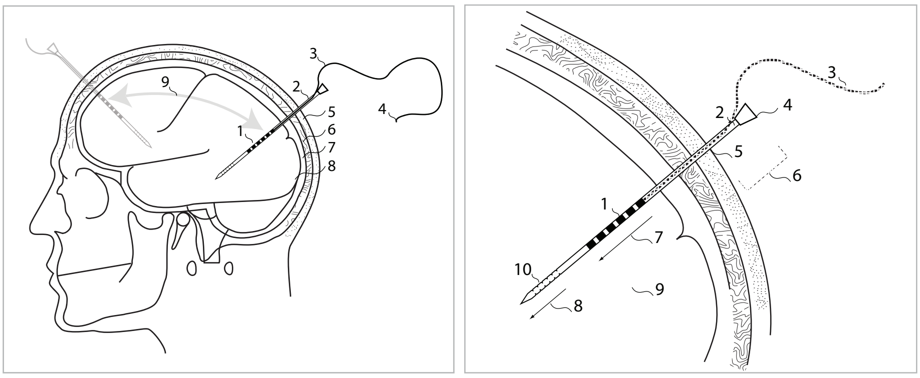


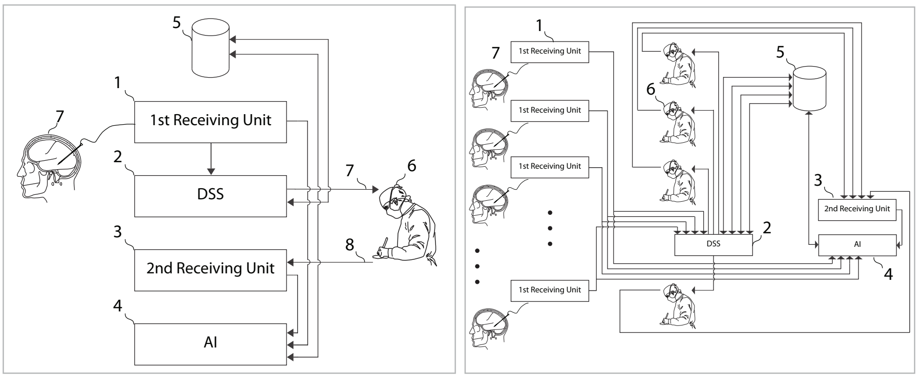
(a) (b)

Fig. 1. *Intracortical Electroencephalograph (ICE) Pin, Side Elevations:* ((a) ICE ***2*** inserted through periostem ***5***, skull ***6***, arachnoid and pia mater ***7*** into brain ***8*** in varying positions ***9***. Receiving electrodes ***1*** encapsulated by brain ***8***. Electrodes ***1*** transmit signals along wire ***3*** to end ***4*** where it is connected to computer. (b) Cannula and internal lumen ***2*** with drainage hole ***4*** and sharpened end ***8***. Electrodes ***1*** at electrode region ***17*** allow insertion through burr hole ***5*** traversing brain ***9***. External region ***6***of cannula remains outside of skull. Connection conductors ***7*** combine into a single wire ***2***. Drainage holes ***10*** in drainage region ***8*** provide openings for fluid to flow ***4***. Support member inserted through ***4*** into internal lumen for accurate placement).

1.1 minedICE Architecture

The authors have tested systems on humans and pigs using Weka, Matlab, RSES and TunedIT to run KDD techniques in the initial interpretation of EEG data. Herein we present a system that, from a high level, dynamically reads and converts EEGs into the time and frequency domains where it compares them to a database and then instructs a DSS to tell the neurosurgeon how confident it is that a particular neurological event is occurring (see Figure 3). If the surgeon provides feedback, it updates the association rules and confidence algorithms making it more intelligent for the next patient. The basis of the architecture has been the author's work using deterministic finite automata [8], [4], [5], [6]. Now the authors move on to detecting life threatening neurological events [7].

Figure 2 $\S(a)$ represents a single patient-to-neurosurgeon view and $\S(b)$ one of many ways a hospital could link multiple patients to multiple neurosurgeons. Signals received at the 1st receiving unit *1* are channeled in real time to two arrays, one in time domain and the other in the frequency domain. A discrete finite automata module segments critical areas for the discretization units autonomous to each of the two time and frequency streams. A first stream of discretized data is compared to a database that contains association rules where an identity ζ, number π located at frequency μ has a confidence of σ. Accordingly, each $(\zeta^{\pi}_{\mu})^{\sigma}$ is passed 1) to update the AI module and 2) to the DSS unit. DSS interpolation: The plurality of $(\zeta^{\pi}_{\mu})^{\sigma}$ are associated with an ontology in the DSS *2* module



(a) (b)

Fig. 2. *Architecture:* ((a) Local architecture: 1st Receiving Unit ***1*** DSS ***2***, 2nd Receiving Unit ***3***, AI module ***4*** central database ***5*** neurosurgeon ***6*** and patient ***7***. DSS connection to Neurosurgeon ***7*** and AI receiver from neurosurgeon ***8***. (b) Hospital WAN: Plurality of 1st Receiving Units ***1*** single DSS server***2***, single 2nd Receiving Unit server ***3***, AI module ***4*** central database ***5*** neurosurgeons ***6*** and patient ***7***. DSS connection ***7*** AI receiver ***8***).

which alerts and tells the neurosurgeon *6* the state and the probability of that data mined neurological state. The 2nd Receiving Unit *3* receives feedback from the neurosurgeon which converts various forms of input back to the $(\zeta_\mu^\pi)^\sigma$ format. Machine Feedback: Utilizing an unsupervised algorithm by the author illustrated in [3] the difference in the confidence level of each σ in $(\zeta_\mu^\pi)^\sigma$ [11], is $\phi(x)$ for each number $\pi \in score$. It is only at this point the database *5* is updated and the associated rules relying on the new $(\zeta_\mu^\pi)^\sigma$ in the 1st receiving unit *1* are updated.

2 Experiments

In order to separate and classify each significant portion of the streaming ICE signal π in terms of the Fast Fourier Transform (FFT) coefficients of the artifact polluting the signal we extract the features of the ICE 4 times for each threshold π before using classical KDD tools as illustrated in Figure 4 to identify each relevant ζ^π where π is compared when $(\pi \in 1, 2.5, 5....10)$ for $n = 256$ and $(\pi \in 1, 2.5, 5....10)$ for $n = 2048$. Next we divide each signal π of the set of selected signals Π into equal-sized non-overlapping hops with size $2n$ samples $\Theta^\pi = \theta_1(\pi), \theta_1(\pi), \theta_2(\pi), ..., \theta_r(\pi)$ where r is the size of $\frac{(\pi)}{2n}$ Once this is repeated for both $n = 256$ and $n = 2048$ for each signal π we pick up hops $\theta_i(\pi)(1 <\leq 1 \leq)r$ such that s hops for π form the set Γ^π $(\Gamma^\pi \subseteq (\Theta^\pi(\Gamma^\pi = (\gamma_1(\pi), \gamma_2(\pi), ..., \gamma_r(\pi))))$. Now that we have picked up our significant hops we perform FFTs on them such that the amplitude of the complex portion is calculated and stored as a pointer. A simple aggregation loop is them performed at

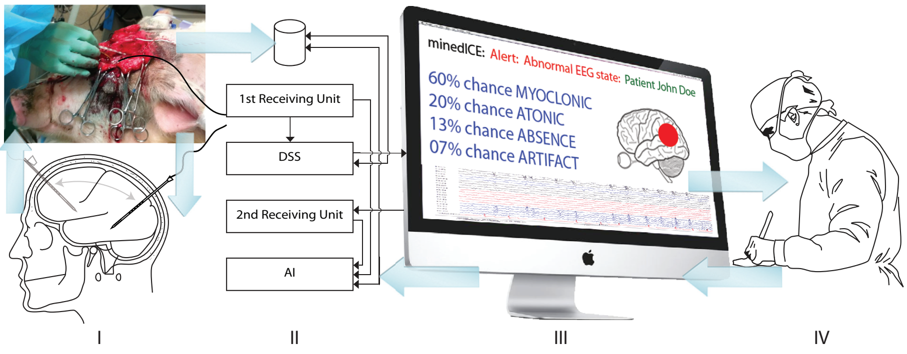


Fig. 3. *Interim Architecture:* I. Learn classifiers between pig / human neurological states. II. 1st Receiving unit sends discretized signal to AI and DSS. III. minedICE procures DSS to neurosurgeon. IV. Neurosurgeon provides feedback.

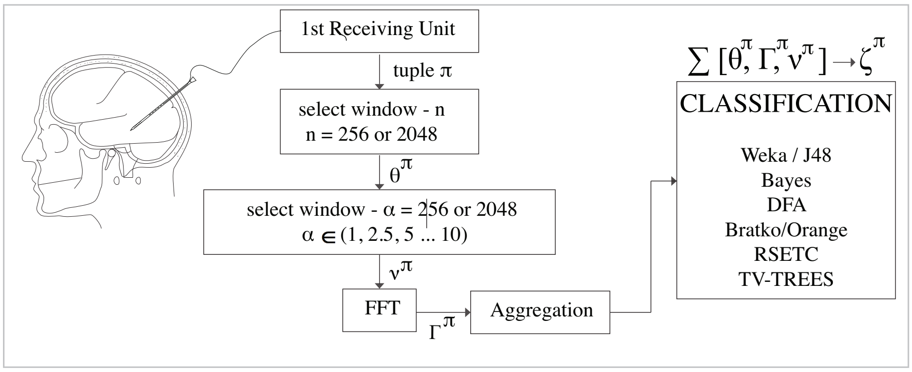


Fig. 4. Receiving Unit to Classification

each pointer as they turn up in the system. The results are now ready for our KDD experiments.

To test the feasibility of the various KDD Tools we used C++ DFA1, SVM Weka/J48, Bayes, DFA, Bratko/Orange and RSETC to build models for each of 9 Reports, made for the purpose of this test wherein the authors provided 9 test junctures in signals wherein the overall curve of the DFA tree resembled an arc. These reports were named according to the Power spectrum at each point. As shown in Figure 5 one sees the Report 11010 etc which acted as the training data and we chose the J48 decision tree as our classification algorithm. To test how the Weka instantiated a tree we found that it did break off at 9 leaves with 12 branches. We were not able to get Orange to output a similar tree. Looking at Figure 5 we see that the Weka /J48 system correlates closest to the training set's general arc. It is interesting and certainly cause for investigation why SVM hsot up, rather than down at Report11011. It is also interesting that DFA, C++

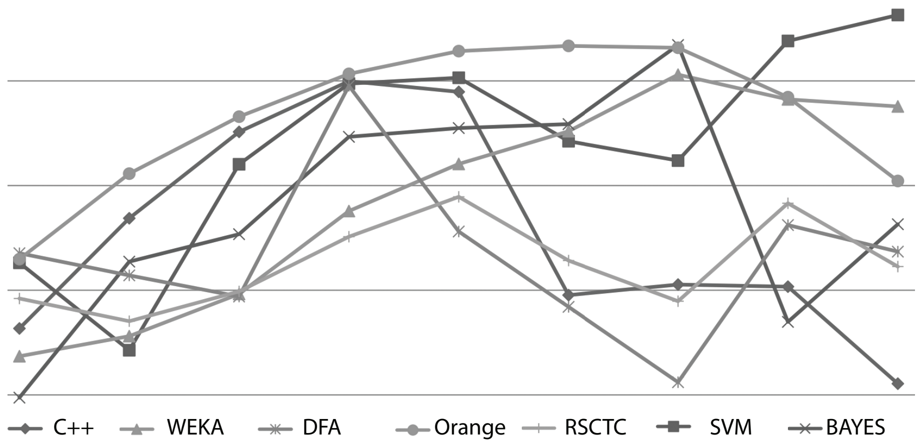


Fig. 5. Receiving Unit to Classification

DFA1, RSES and Bayes are clumped together after Report11011 in the 1,000 to 2,000 range. It is also interesting that at Report 11110, apart from Bayes, Bratco/Orange, and C++ DFA 1, all the KDD tool nailed it on 2,500 perfectly.

3 Conclusion and Future Work

The system is able to datamine a stream of signals and pickup the correct patterns from within FFT's. This is the good news. The bad news is that these tools' results should have been much closer. Our future work will be to analyze why the disparities of the experiments existed. Also we were not able to match the data in a form to work with Action Rules as in the past [1], [9]. This may turn out to be crucial because as the crucial element in minedICE is that the system must learn [2]. As the system learns and makes new rules some of the form of Action Rules or TV Trees may be necessary to manipulate the tree for the DFA. We may find that Weka/J48 is not the best when we correct out possible errors. We may also find that out methodology of converting the signals into FFTs for the classification module is inherently flawed. Essentially we need to run these tests a lot more and make the system more robust. Again though, we know that as each set of tests are concluded the machine is getting to the point that it will read actual human data and possible save lives.

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