DOI 10.31256/UKRAS19.3

A Bioinspired Approach for Mental Emotional State Perception towards Social Awareness in Robotics

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Abstract— **This preliminary study explores a new approach to EEG data classification by using the concept of evolutionary algorithms to perform attribute selection, as well as optimise a neural network for data classification in mental communication for robotics. EEG brainwave data is recorded from a preliminary set of subjects via the TP9, AF7, AF8, and TP10 electrodes used by the EEG headband, and 2550 statistical temporal features are extracted as dimensions of data. Nature inspired evolutionary algorithms select attributes before an evolutionary algorithm optimizes a neural network topology. A Long Short-Term Neural Network is also trained to perform deep learning on the data. Promising results show that the evolutionary optimised neural net scores 96.11% accuracy and the LSTM achieves 96.86%. The evolutionary neural network, although lacking in 0.75 accuracy points, has a training time far more optimal than the LSTM, at less than 25% of the required resource usage.**

I. INTRODUCTION

While deep learning is often applied to solve extremely complex problems, the procedure is often criticized for being expensive in computational resources and processing time requirements; due to the growing need for machine learning in both industrial and scientific applications of robotics, optimization is at the forefront of importance for their viability. Natural optimization, such as that observed in Darwinian evolution, are now becoming a viable option for solving real-world problems.

In Human-Robot Interaction (HRI), an increase in resource availability allows for the development of more degrees of interaction with a human, as well as the accuracy of classifying those discrete interactions, for example, in using complex techniques to classify a user's thought patterns as a point of input in social interaction with machines. Specifically, to classify a subject's emotional state requires a large amount of data to be processed in order to train a model which can then match minute patterns and rules to those states. Since the EEG signals are complex, non-linear, and non-stationary, temporal time-window and statistical extraction techniques must be employed in order to mathematically describe a wave pattern.

This paper presents a preliminary study in which an evolutionary simulation from a previous study derives, through a *survival of the fittest*, a fully connected neural network topology which can classify a dataset of an EEG brainwaves to emotional state. The accuracy closely matches that of modern deep learning techniques but is trained in under a quarter of the computational resources required.

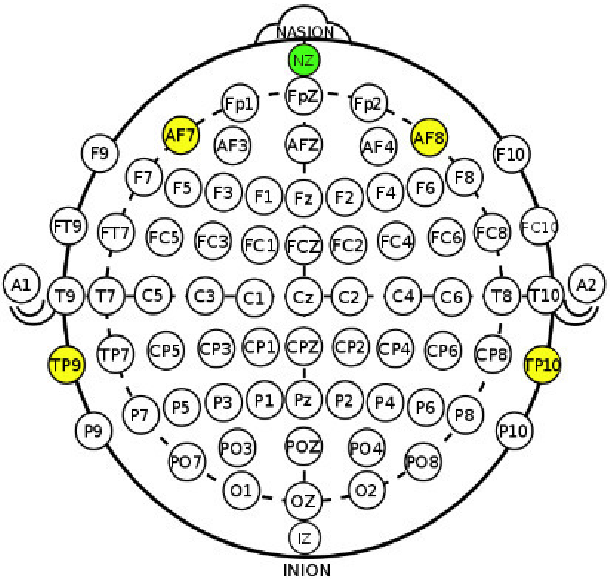

Fig 1. EEG sensors TP9, AF7, AF8 and TP10 of the MUSE headband.

II. BACKGROUND

Electroencephalography, or EEG, is the measurement and recording of electrical activity produced by the brain [1]. Electrodes are placed on certain points around the cranium, which read minute electrophysiological currents produced by the brain due to nervous oscillation [2]. Raw electrical data is measured in Microvolts (uV), which over time produce wave patterns when gathered sequentially.

The MUSE is a commercially available EEG headband featuring four electrodes for recording brainwave activity, as seen in Fig 1. Placement positions correlate to the international standard EEG placement system [3].

Neuroscientific studies show that chemical composition influences nervous oscillation, which in turn generate

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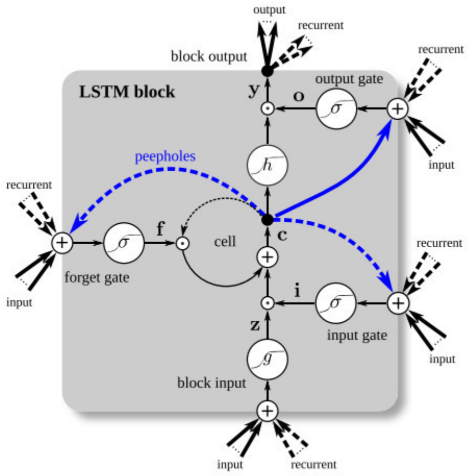

Fig 2. An illustrated LSTM unit [14]

electrical brainwave activity [13]. Emotions are a direct result of varying chemical compositions within the brain, and thus a side-effect of feeling emotion is to generate electrical brain activity, which can then be reverse engineered and classified and their source emotion(s).

In terms of emotional classification through different levels of user enjoyment, researchers successfully measured two distinct states of varying enjoyment of a task via binary classification techniques [4]. Muse headbands are also often used in neuroscience research projects due to their low cost, accessibility, and effectiveness in terms of classification and accuracy. In a related experiment, binary classification of two physical tasks achieved 95% accuracy using Bayesian probability methods [5].

A previous study used ensemble classification techniques to classify a user's emotional state, providing the dataset for this experiment [6], the best model was a Random Forest classifier with a classification accuracy of 97.89%. A related study also used classical machine learning techniques to classify whether someone was concentrative or relaxed [7] with success following the same method of statistical extraction.

Long-Short-Term-Memory (LSTM) is a technique in which multiple recurrent neural networks (RNN) predict an output based on their input and their current state. An illustration of the individual LSTM units can be observed in Figure 2, the operations that each unit will compute are given as follows.

Firstly, a logical forget will decide which information to discard and delete: W_f represents the learning-weighting matrix, h represents the output vector of the unit at provided timestep $t-1$, x_t being the current input vector, and finally b_f is a bias vector applied to the process.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (1)$$

The cell then stores certain information, i represents input data, with C_t being the vector of the new values generated by the process.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

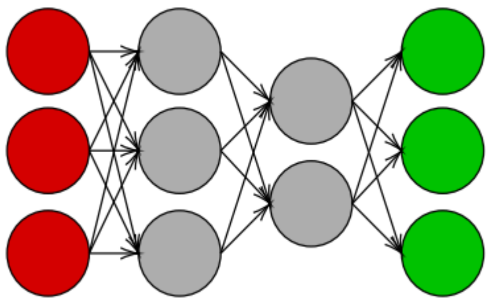

Fig 3. A Fully Connected Neural Network for classification of Three Inputs to Three Classes, with Two Hidden Layers of 3 and 2 Neurons

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c). \quad (3)$$

The cell is then updated using (1-3) in a convolutional operation:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (4)$$

An output is consequently generated where O_t represents the cell's output gate. The internal (hidden) state of the cell is subsequently updated:

$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o). \quad (5)$$

$$h_t = o_t * \tanh(C_t). \quad (6)$$

Fully Connected Artificial Neural Networks (ANN) also approximate and classify, though do not compute temporal states as with LSTM. An example of ANN architecture can be seen in Figure 3, where three inputs are computed to one of three output classes, via two hidden layers of 3 and 2 neurons respectively.

Learning is performed through backpropagation [8]. This is a case of automatic differentiation in which errors in classification or regression (when comparing outputs of a network to ground truths) are passed backwards from the final layer, to derive a gradient which is then used to calculate neuron weights within the network, dictating their activation. It must be noted that the network topology itself is static, and thus, is not optimized. Weighting refinement is carried out via the following process:

1. Generate a network; input nodes are equal to the number of data attributes, outputs are equal to the number of classes (or 1 for regression problems). Hidden layers, if any, are defined by human input.
2. Initialise the node weights randomly by a specified distribution algorithm (e.g. XAVIER).
3. Compute the gradients.
4. Backpropagate the errors through the network to update neuron weights.

Errors are calculated via various methods, e.g. distance from the ground truth where real numbers are concerned. For classification, entropy is calculated:

$$E(S) = -\sum_{i=1}^{c} P_i \text{ x } log_2(P_i)\,. \quad (7)$$

Comparison is thus the difference between two entropies, giving information gain or information loss when one model is compared to another. This is the value of the Kullback-Leibler (KL) divergence when a univariate probability distribution of a given attribute is compared to another [10]. Information gain is thus given as:

$$InfoGain(T, a) = H(T) - H(T|a). \tag{8}$$

Evolutionary algorithms search a problem space via a method inspired by natural evolution [11]. A population of solutions have a fitness metric and compete against one another for survival. This causes a race condition to occur when an environment can support fewer solutions than exist, the *survival of the fittest*, causing weaker solutions to be killed off and allowing the stronger to survive. This, over time, causes the population to increase in strength [12].

The evolutionary search in its simplest form follows this general process:

1. Population at generation 0 are initialized via a chosen distribution, e.g. Random.
2. The simulation begins until a defined termination:
    a. Select parent(s) for use in generating offspring.
    b. Evaluate the generated offspring's fitness.
    c. Kill off the weakest members based on the number of solutions that the environment can support.
3. Produce the strongest solution found after the simulation is terminated.

Previous work found success in evolutionary optimisation algorithms being applied to the selection of network topology in a single-objective approach to achieve the highest classification accuracy, and thus best applied to datasets in which class distribution is close to equal [9]. The problem space of deep neural networks grows exponentially with each added layer, and thus, an exhaustive search is an unrealistic option in terms of even the most state-of-the-art computer hardware. For this reason, heuristic search techniques are employed to efficiently explore the problem space.

III. Method

Data is acquired from a previous experiment [6]. Data is gathered from two subjects, male and female aged 20-22. The EEG data was recorded from a MUSE EEG headband where each subject viewed six films clips all with an obvious emotional valence. The emotional experiences caused by the clips formed a database of raw electrical readings which then had temporal statistics extracted. Statistical features extraction derived by [7] was adopted in this work.

As stated in [7], a time window of length 1s was introduced, overlapping every 0.5 seconds (e.g. *w1 0-1*, *w2 0.5-1.5*). Time windows are described by their extracted mathematical statistical features. Of the 2550 features generated for each object of data, an evolutionary search of 10 solution population members was performed for 10 generations to calculate the best set of features, since the dimensionality of the data was far too complex.

Two alternative models are explored and then trained with the generated dataset. Firstly, an LSTM topology is manually explored and tuned, as the models are far too computationally expensive to search with a metaheuristic approach. Secondly, the evolutionary algorithm will search the problem space of MLP neural networks, with a limitation of three maximum hidden layers a 100-neuron upper bound for each. A population of 10 are simulated for 10 generations, with roulette selection being used for breeding partners. The simulation is run three times with identical parameters for scientific validity. Both models are trained on 10-fold cross validation of the dataset, and finally compared in terms of classification accuracy and resources required to train. Both types of network are given 50 epochs to train, with a batch size of 50 for prediction. All random numbers were generated by the Java Virtual Machine (JVM) with a seed of 0.

Both models were trained on a Graphical Processing Unit (GPU) due to its high efficiency when compared to a Central Processing Unit (CPU). The GPU used was an Nvidia GTX1060 with 6GB of Graphical Memory and 1280 CUDA cores for computation. Displaying the OS (Windows 10) was the only other graphical process executing during the experiment.

IV. Results

Evolutionary attribute selection performed on the dataset for 10 generations with a population of 10 found 500 attributes suitable for use in classification, and thus data dimensionality was reduced from 2550 to 500 for the dataset to be used in the experiments.

Manual tuning of the LSTM found that a single hidden layer of units consistently outperformed deeper networks. 25 units on the layer were found to be the most optimal, with a classification accuracy of 96.86%, as seen in Table I.

Three genetic simulations were executed as observed in Table II, the most optimal network was found to be a single hidden layer of 15 neurons, producing a classification accuracy of 96.11%.

Finally, the two best networks are compared in Table III, where, although slightly more accurate (+0.75), the LSTM took far longer to train (+48.45s).

V. Conclusion

To conclude, this experiment suggested two models for classifying a subject's mental emotional state based on the mathematical descriptions of recorded brainwave activity:

- An LSTM that achieved 96.86% and required 65.11s of resources to train
- An MLP with genetically optimised topology which achieved 96.11% and required 16.66s to train.

TABLE I. MANUAL TUNING RESULTS FOR LSTM TOPOLOGY FOR EMOTIONAL STATE CLASSIFICATION

LSTM Units	Classification Accuracy (%)
25	**96.86**
50	96.66
75	96.48
100	95.73
125	95.87

TABLE II. THE BEST SOLUTIONS OF MLP TOPOLOGY AT THE FINAL GENERATION OF THREE INDIVIDUAL EVOLUTIONARY SIMULATIONS

MLP Topology	Classification Accuracy (%)
1 hidden layer, 6 neurons	95.68
1 hidden layer, 15 neurons	**96.11**
2 hidden layers, (9, 5) neurons	94.37

TABLE III. COMPARISON OF TWO FINAL SOLUTIONS

Classifier	Classification Accuracy (%)	Training Time (s)
LSTM (Manual)	**96.86**	65.11
MLP (Genetic)	96.11	**16.66**

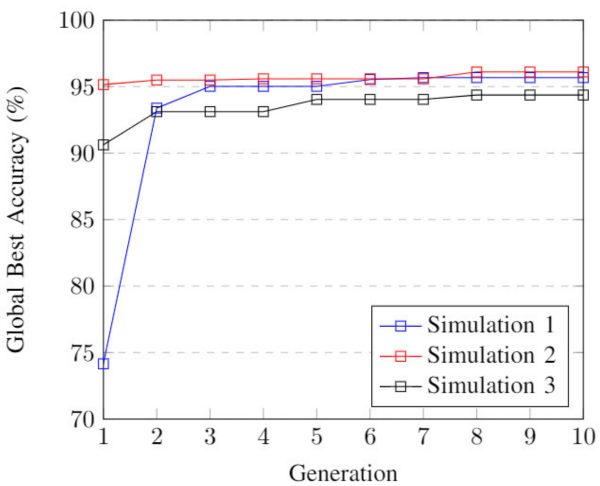

Fig 4. Three evolutionary simulations run on the dataset

Although the LSTM is slightly more accurate at prediction, the optmised MLP managed to classify with close accuracy in around one quarter of the required resources to train. Future work should concern applying the two experiments to larger datasets as well as problems of different dimensions, comparing the difference in classification ability and resource usage, and finally analysing the patterns observed between problem spaces. With enough computational resources available, the genetic search should be applied to the LSTM topology for a true comparison. Additionally, a multi-objective approach should be explored, not only concerning accuracy, but also efficiency in terms of resource usage. With an accurate model to classify Mental Emotional States, the next step is to endow a robot to socially interact to humans (i.e. by selecting proper (inter)actions) based on their feelings in order to provide some assistance (e.g. health care contexts: monitoring elderly mental health; assisting clinical sessions with children, etc.).

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