

Human-Computer Interaction with Special Emphasis on Converting Brain Signals to Speech

Venkatesh Sharma, Kumar Sambhav Jain, Amrita Kaur, Ashima Singh



Abstract: Huge hurdle neuro engineers face on the road to effective brain-computer interfaces is attempting to translate the big selection of signals made by our brain into words pictures which may be simply communicable. The science-fiction plan of having the ability to manage devices or communicate with others simply by thinking is slowly but surely, obtaining nearer to reality. Translating brainwaves into words has been another large challenge for researchers, but again with the help of machine learning algorithms, superb advances are seen in recent years. The exploitation of deep learning and acceptable machine learning algorithms, the management signals from the brain will regenerate to some actions or some speech or text. For this, a neural network is created for the brain and conjointly a mapping is completed to catch all the brain signals in which neural network will be additionally used for changing these signals into actions. From the past literature, it is being concluded that the Deep Neural Networks are one of the main algorithms that are being placed into use for this research. This review article majorly focuses on studying the behavioral patterns generated by the brain signals and how they can be converted into actions effectively so that people suffering from semi or full paralysis can use this technology to live a normal life if not completely but to a certain extent. Also, it focuses on analyzing and drawing a comparison between linear and non-linear models and to conclude the best-suited model for the same currently available to the researchers.

Keywords: Brain, Human-Computer Interaction, Deep Neural Networks, Brain-Computer Interaction, Linear Auditory, Linear Vocoder, DNN Auditory, DNN Vocoder.

I. INTRODUCTION

Today almost more than 1.9 percent of the total population is paralytic or is even suffering from a problem in which they can't move or speak [1]. Many suffering from this problem might get benefit from technologies that would help them in some of the daily activities but at the same time these high-end devices are not always sufficient to meet the needs of the paralytic people and there is an urgent need of introducing a system through which brain signals can be converted into actions. With the growing dependence on the use of technology, everyone desires to have easy operable electronic devices and one of the easiest is to give brain commands these electronic devices [2].

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Users might desire to operate these electronic devices automatically i.e.

with the commands given through the brain and they don't have to do anything manually. Scientists and many engineers have been constantly working hard to crack this and steps have been successfully achieved in brain-computer interface (BCI) which is responsible for establishing a connection between the brain and any electronic device.

Forget about using keyboard, mouse or touchscreen and imagine a future in which we just use our brain commands to control electronic gadgets [2].

Neuroscience is the field that deals with the study of the nervous system [1]. With the new technology rising such as Brain-Computer Interface (BCI) systems there is a lot of advancement and resembles a huge scope of research [2], [3]. But analyzing and interpreting data collected from these BCI systems is not an easy job, so many software tools are being emerged to ease the scientists in the field. These transmitted brain signals must be converted to speech or some text according to which some actions can be taken. For a long time, many neuro engineers are already trying to convert the brain signals to actions and it has become a huge hurdle in understanding the signs of the paralytic person [4]. For this many high-end prosthetic devices have been discovered but none of them have provided an efficiency which was required [1].

The brain consists of a million neurons that possess capabilities such as concentration or thinking communicating with each other using electricity [2]. These neurons send electrical signals altogether to produce electrical activity for performing mental operations in the brain. The brain is like an electrical device and uses electricity as the source of communication to the electronic devices. The electrical activity that the brain possesses is performed via a phenomenon known as Brainwave pattern [4]-[6]. The electric waves which are produced in the brain emit many small electrochemical impulses of varying frequencies and can be detected by electroencephalogram [6]. Recent advances by neuro engineers in the field are making this idea into reality, opening the door to restoring brain commands to electrical signals and thus performing actions [4]-[7]. People suffering from Parkinson's disease and people who are deaf are growing exponentially [8]. To regulate the brain activities using electronic devices brain-computer interface is developing and is continuously researched for applications such as lie detector or even human augmentation [4]. A brain-computer interface (BCI), a subsidiary of the human-computer interface helps in establishing direct communication between the brain and the external device of the brain that can be converted into speech [4]-[5]. The brain-computer interface is used as a communicating agent between a brain and an object that directs any external activity such as control of the cursor.

When millions of neurons within the brain try to communicate with each other, measurable electric currents patterns called brain waves are created. There are numerous ways to collect brain signals but one of the most popular is to use Electroencephalography (EEG) [5]-[6]. This method tries to detect the presence of electrical signals using the electrodes that are attached to the surface of the brain in different regions.

The brainwave patterns include delta, theta, alpha, and beta and there are wirelessly sent signals to the electronic devices to control and interpret them [7]. This interface permits the communication pathway between the controlling object and the brain. These activities show the BCI principles and when they work, they are an example of brain neurons working together to merge to give an electrical activity [1]-[3]. Controlling electrical devices using brain commands or with just thought would not only be most convenient for severely disabled people but one of the most important breakthroughs in this field of neuroscience.

The signals produced from the brain detected by EEG are the potential difference between different regions of the cortex which are produced due to the continuous flow of ions between the millions of neurons. Whenever any neuron is produced or activated, it generates a potential that is propagated to ions of other neurons which further provokes a huge flow of information about the different parts of the cortex. The acquiring records are the intensity of brainwaves and are read by the electrodes and vary between $0\ \mu\text{V}$ and $200\ \mu\text{V}$, with a frequency range between 0.3Hz to 100Hz [7]. If there is a peak read in EEG, it indicates a spatial location of brain activity because these activities happen due to millions of neurons start communicating with each other [7], [8].

Thus, brain-machine interfaces are a technology that translates brain signals into actions, like moving a cursor on a screen [8]. They have been used earlier for paralytic people or even for people suffering from Parkinson's disease but at only eight words per minute but now with this advancement of the speech recognition system, the number has risen to one hundred and fifty words per minute [4]-[7].

II. LITERATURE SURVEY

The following section covers a detailed literature survey, encompassing the problems associated with the work, the work is done so far in the field of Human-Computer Interaction (HCI) and the problems that have been identified.

An Introduction

With the ever-growing technology and fast pacing lives, the people around the globe are becoming prone to diseases now more than ever. But with the advent of advanced problems came advanced solutions. Where a decade back, the problems like that of paralysis especially that dealing with complete paralysis and ALS (Amyotrophic Lateral Sclerosis), in which the person loses the motor ability of the muscles and is incapable of showing any kind of movements in the body, were considered as incurable and the person was subject to a rather dependent life, can now to an extent lead an independent life in terms of doing daily chores like that of communicating messages or moving around [5]. The kind of technology available today and the amount of investment, be it financial or in terms of knowledge and

research, being made in the field of brain signal mapping has increased many folds and now with techniques such as that of BCI (Brain-Computer Interfacing) and HCI (Human-Computer Interaction) it has become possible to rejuvenate the motor senses of the dead muscles just by analyzing and reading the neuron impulses from the brain and converting them into movements with the help of machines and smart devices [4], [5]. The BCI field relies on the brain's ability to give rise to some types of responses through the neurons, which the computers can then harness and interpret [5]. The neurons regulate most of the body's motions and functions. Through chemical and electrical signals, they transmit information to and from the brain and the rest of the communication system. Scientists can use new technologies to manipulate these muscle impulses to power devices, much like how the brain regulates muscles [6], [7]. The apprehension of how the brain controls movement led to tools and algorithms being created that can be realized on a computer to identify these patterns in brain cell behavior and then move an artificial body accordingly. The techniques used to study these brain cells can be categorized into two forms, one being the invasive method and the other the non-invasive method. In the non-invasive method, the subject is fitted with an "Electroencephalogram" or EEG cap, which records brain signals when electrodes are attached on the scalp of the brain [4]-[5]. The subject is then exposed to a series of Yes/No questions flashed in a sequence on the screen fitted with two bulbs on either side, with emitted light of different frequencies.

The subject responds to the question when a question appears on the screen by looking at one of the bulbs that corresponds to either of the two (yes/no) [8]. The intensity of that particular light is picked up by the visual cortex in the brain and determined by the EEG cap when the subject's eyes are forced to focus on one of the lights. [2] This signal is interpreted by the computer and moves the cursor in the response direction.

The use of an EEG cap is not the only way to measure brain activity, the "Electrocorticography" invasive method is used [2], [4]. It also tracks brain activity because, unlike the EEG mask, it is surgically placed directly on the surface of the brain and is in constant contact with the various parts of the brain producing visual and speech stimuli, providing a clearer signal and more accurate information. This technology is put to use wherein the assistive devices enable the subject to type sentences letter by letter, by focusing on the different frequency lights each corresponding to a particular letter, at up to 10 words per minute. But that's a far cry from everyday conversations which take place at about 150 words per minute.

To overcome this problem, researches from around the world started focusing on converting the brain signals directly to speech. New research from UC San Francisco shows that it is possible to generate synthesized speech from brain signals directly [1]. Brain signals precisely co-ordinate nearly 100 muscles to move the lips, jaw, tongue, and larynx, shaping our breath into sounds that form our words and sentences [2],[3]. In the UCSF study, volunteer participants being treated for epilepsy read sentences out loud while the "Electrocorticography" was being used to measure the resulting signal patterns [4].

A computational model based on the data (signal pattern) enabled the scientists to decode how activity patterns in the brain speech centres contribute to the particular movement of the vocal tract. These simulated vocal tract movements were transmuted into sounds to generate intelligible synthesized speech. The sound patterns of the individual

words synthesized from the brain activity were remarkably similar to the original, spoken sentences.

B Research Findings for Existing Literature

Table 1. discuss the systematic review of the state-of-the-art methodologies.

TABLE 1: A Literature Review Of The State-Of-The-Art Methods

S.No	Paper Title	Tools/Techniques Used	Findings	Future Scope
1.	Influence of Context and Behavior on Stimulus Reconstruction from Neural Activity in Primary Auditory Cortex. [1]	Surgery, Neurophysiological recording, Auditory stimuli, and analysis, Reconstructing sound spectrograms using optimal stimulus priors	Contrasting stimulus reconstructions under various behavioral states revealed a novel view of the rapid changes inattentive and motivational state-induced Spectro-temporal response properties.	The proposed algorithm needs to be tested critically for future findings.
2.	Progress in speech decoding from the electrocorticogram. [2]	Electrocorticogram	Decode aspects of speech directly from neural activity to the development of neuroprosthetic devices for people with severe neuromuscular disorders and communication.	The computational model of neurological speed processing needs to be improved for more accurate decoding
3.	Neurolinguistic and machine-learning perspectives on direct speech BCIs for the restoration of naturalistic communication. [3]	ECoG, Electrodes	Research to restore speech to develop devices that can reconstruct spontaneous, naturally spoken language from the underlying neuronal signals	BCI technology is now progressing into autonomous wireless implants, which are feasible in the near future.
4.	Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups. [4]	DNN, HMM, Phonetic Classification and Recognition on Timit, GMM	How three major research groups made substantial improvements in several state-of-the-art ASR systems by replacing GMMs with DNNs	The biggest drawback of DNNs relative to GMMs is that the massive scale machines are much harder to use in mass datasets to train them.
5.	Speaker-Independent Speech Separation with Deep Attractor Network. [5]	Single-channel speech separation, Deep Attractor Network	Evaluate the process of two and three speaker mixtures using the Wall Street Journal dataset (WSJ0) and equate it with other speech separation approaches.	The investigation of speaker knowledge can be integrated into the calculation of anchor points and embedding into generation.
6.	Discrimination of speech from nonspeech based on multiscale Spectro-temporal Modulations. [6]	Multilinear Tensor Analysis, DNN, GMM	The auditory model's advantages over the other two models, especially at low signal-to-noise (SNR) ratios and high reverberation.	The proposed model needs to be analyzed and tested more critically

7.	An Algorithm for Predicting the Intelligibility of Speech Masked by Modulated Noise Maskers. [7]	Time-Frequency Normalized Spectrograms, Intelligibility Subspace Decomposition	The proposed algorithm shows similarities to the algorithm of short-term objective intelligibility (STOI), but it works for a wider range of input signals.	To test the efficiency of the proposed intelligibility prediction over data sets with different types of distortion.
8.	Localization and classification of phonemes using high spatial resolution electrocorticography (ECoG) grids. [8]	ECoG, Fast Fourier Transform, Signal Processing, BCI	Cortical activity results during the pronunciation of phonemes, documented using miniaturized electrocorticography grids with a high spatial resolution	Future research on superior grids can show additional separability
9.	Auditory representations of acoustic signals. [9]	An analytically tractable framework, method of convex projection	The functional significance of the different stages of auditory processing.	The algorithms were designed to test acoustic spectrum quality at all processing stages that need to be tested critically.
10.	Classification of auditory steady-state responses to speech data. [13]	Auditory Stimuli, Finite Impulse Response filter, Common Spatial pattern, Linear Discriminant Analysis	Classification of ASSR responses with 78.6±5.32 percent accuracy.	Major planning to develop an auditory BCI program using auditory instructions.

C Summary

Starting from treating paralysis as incurable to landing up helping them have their voice heard again, technology has come a long way. The real breakthrough that came was the use of non-invasive methods like that of EEG (Electroencephalogram) wherein the electric pulses from the brain neurons were subject to detection and interpretation with the help of Deep Neural Networks [14], [15]. But even though this enabled the patients to speak only by imagining and reading out loud the data in their mind, the rate at which this was carried out was very slow at about 10 words per minute. This led to the researchers switch to invasive methods like that of Electrocorticography to convert brain signals directly to speech. The results from these researches have shown that the speech that was artificially synthesized with the help of ECoG was very similar to the original untampered voice sample.

The brain auditory cortex is that part of the brain that converts audio directly into signals. The motor cortex which handles the movement of lips, jaws, vocal cords is the most important part to be researched and handles how brain signals can be transmitted and converted to speech. The speech is reconstructed from the neural responses and regains the possibility of using this technique as a speech brain-computer interface to restore speech in the case of ALS patients.

For measuring the reconstruction accuracy, the two factors were examined:

- 1) The regression technique (linear versus nonlinear deep neural network)
- 2) How any speech intended for reconstruction is represented.

III. OUR CONTRIBUTION

1. The purpose to find a way that the brain signals can be directly converted into actions using speech recognition. For this, we aim to study an artificial algorithm and finds which algorithm will be able to transmit the brain signals into speech successfully.

2. The Research of different techniques used by neuro-engineers to translate brain signals into voice and then communicate effectively into actions and also to find which model will be best suited for finding reconstruction parameters i.e. either linear or non-linear regression model.

IV. RESEARCH METHODOLOGY

Brain-Computer interfaces a part of the human-computer interface is a technology that will be used to convert the brain signals into speech and auditory reconstruction an inverse mapping technique results in the rough approximation of the acoustic stimulus by examining the evoked neural activity.

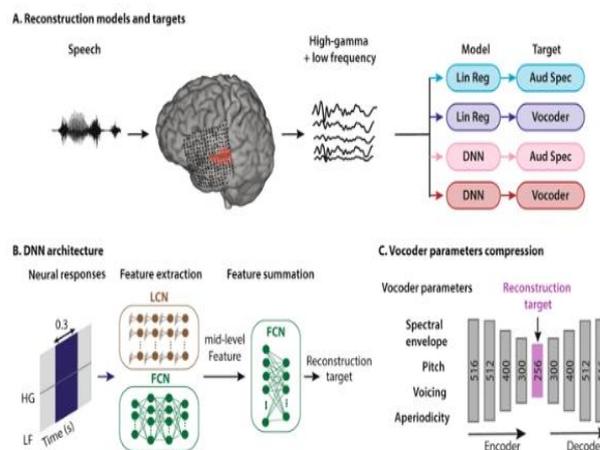


Fig 1. Non-Linear Regression Model [11]

The above fig 1. describes the schematic representation of the speech reconstruction method [11].

In context with this image, the process was divided into three parts which include:

(A) Patients are made to listen to natural speech sentences. The human auditory cortex was then used to reconstruct the speech stimulus. The electrodes were attached to different parts of the brain and are shown in red in the figure and at the same time high and low-frequency bands were examined from the neural activity. There are two types of regression models, one linear and non-linear, with two speech representations, resulting in four combinations [16], [17], one of which is linear regression to auditory (Linear Auditory (LA)) (light blue), other being linear regression to vocoder (Linear Regression Vocoder (LRV)) (dark blue), third one be DNN to auditory (DNN Auditory (DNNA)) (pink) and last one from DNN to vocoder (DNN Vocoder (DNNV)) (dark red).

(B) The feedback for all versions was a low-and high-gamma sliding screen. The architecture of the DNN consisted of two modules [14], namely extracting features and feature summation networks. The first of these two was a fully connected neural network (FCN) for the auditory spectrogram. At the same time, the feature extraction network for vocoder reconstruction consisted of an FCN concatenated with a Locally Connected Network (LCN) and a two-layer neural network fully connected.

(C) Fundamental frequency, spectral envelope present with an autoencoder with a bottleneck layer and voicing were few of the vocoder parameters that were used for conversion of 516 parameters to 256. The layer was used as a target and parameters were found out by the decoder part of the autoencoder network.

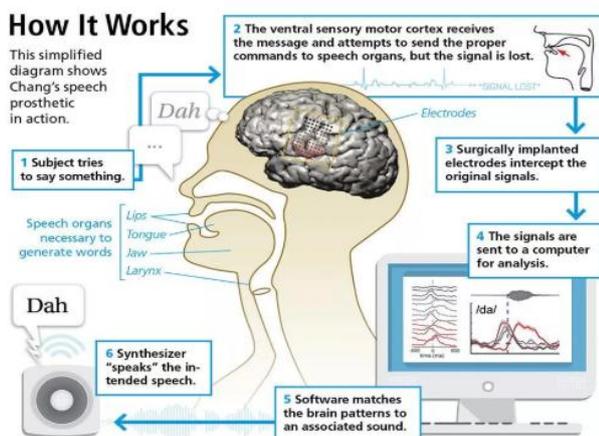


Fig 2. How the process works [12]

The electrodes were made to connect on the surface of the brain as shown in fig 2. [12]. As this method is a part of the invasive technique it follows the process of electrocorticography and performs the following steps:

1. The subject tries to say something
2. The ventral sensory-motor cortex receives the message and tries to give the correct instructions to the organs of speech.
3. Electrodes that are attached on the surface of the brain then intercepts the signals.
4. The computer system receives signals for analyzing.
5. The system then matches the given brain pattern to the sounds already recorded.
6. The intended speech is spoken by the synthesizer.

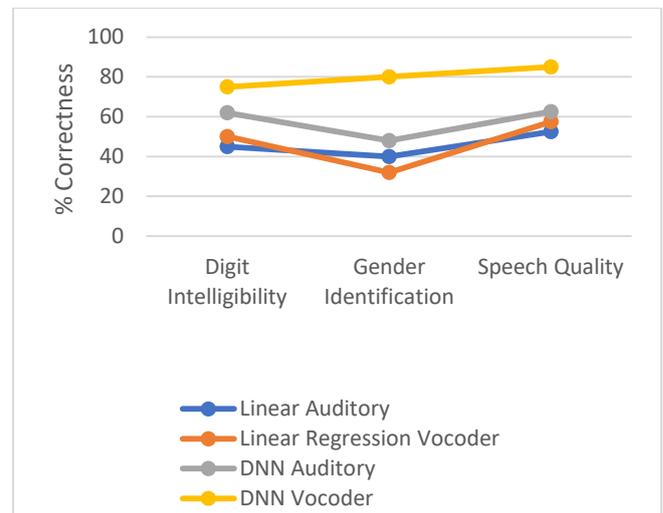
The model test data consisted of continuous speech sentences and isolated digital sounds. For the evaluation of reconstruction models, eight sentences were used. The sentences were repeated continuously and the average of all the repetitions was taken to reduce the consequences of neural noise. There were almost 40-digit sounds, that were given by four different speakers and their sounds were not included in the training and were instead used as a test set for the examination of subjective intelligibility and also to examine the quality of the models. The low-frequency components pulled out by sieving the neural signals and the other high gamma envelope was examined by the Hilbert envelope.

A comparison of linear and non-linear regression models was made with a linear regression model that found a mapping between the response of a neuron population to stimulus representation. There, the main objective was to minimize the mean-squared deviation between the initial stimulus and the replicated one.

The non-linear regression method used as a deep neural network, and we followed two stages of extraction of features and summation of features to construct such a model. The mid-level features are calculated and were used as an input for regressing of the output of the model. The input was given to the feature summation network which was a two-layer fully connected network with batch normalization, regularization and also dropout techniques.

For achieving and calculating the best results different non-linear regression models were compared and also to find an optimal solution for converting brain signals into speech using the invasive technique with the use of electrocorticography. So, the following process was used in the transmission of brain signals into speech using brain-machine interfacing.

V. RESULTS & DISCUSSION



Graph 1. Linear Vs Non-Linear Models

The above graph is a result of the analysis done based on linear vs non-linear models. For this, as a part of the experimental analysis, the subjects were exposed to 4 different sounds comprising of 2 male and 2 female sounds. They were then told to recognize the digits from the sounds produced by the aforementioned males and females.

The Digit Intelligibility was then marked as a percentage of the number of digits correctly recognized out of the total digit sounds produced.

The Speech quality signifies the score of the same on the mean-opinion-scale which was then converted into a percentage scale. Also, gender identification emphasizes recognizing the gender of the digital sound, the result of which was also plotted as the percentage of the times the gender was correctly identified. From the above graph, it is clear that the DNN vocoder is by-far the best in digit intelligibility, speech quality and gender identification leaving behind all its counterpart by a margin. It can be seen that the digit intelligibility of the DNN Vocoder is 75% which is 67% more than the baseline model the LAS, also the speech quality marks the highest score of 85% and even in gender identification the mark is high at 80%. The consequence of the above analysis and research on the different methodologies applied can be seen that a DNN (Deep Neural Network) [19], which unequivocally estimates the parameters of a speech synthesizer from all the flexible neural frequencies, conquers the highest subjective and objective scores on a task of visual recognition, increasing the intelligibility by 65 percent over the base method which used linear regression to recreate the aural spectrum. The efficacy of deep learning and speech generation algorithms to synthesize the next generation of speech BCI systems that can be seen from the demonstration of the above test, which not only rejuvenates a paralyzed patient's vocals and interactions but also has the potential to transform HCI technologies.

VI. CONCLUSION

A correlation between the output of linear regression and nonlinear regression (DNN) models [17,18] in the reconstruction of auditory spectrogram and vocoder representation of speech signals led to the conclusion that using a deep neural network model to regress vocoder parameters significantly outperformed linear regression and auditory spectrogram representation of expression, resulting in 75 perceptions. The findings of the comparisons made were consistent with those of earlier reconstruction research in which the focus was the significance of nonlinear neural decoding techniques. The previous methods used vector support machines, linear discriminant analysis, linear regression, nonlinear embedding, and classifiers for Bayes. In recent years, in many brain-computer interfaces technologies, deep learning has shown tremendous success, and our study has extended this trend by showing the benefit of deep learning in speech neuro-prosthesis research. The illustration of the fact that the accuracy of the reconstruction depends on both the number of electrodes and the duration of training data was previously made in this paper. It is remarkable how consistent this paper is with the findings of studies showing the superior advantage of deep learning models over other techniques, especially when there is a large amount of data. A key point to note was also that the rate of improvement slows down as the number of electrodes increases, which could reflect the small range of neural responses in our recording which eventually restricts the additional information obtained from additional electrodes. In contrast, increasing the number of electrodes also increases the complexity of the neural network model and the number of free parameters. Because of the limited

duration of our training data, more training data may be required before the benefit of additional features becomes apparent. The paper further illustrates that taking the amount of training data a notch higher results in better accuracy (measure to calculate the performance) of the reconstruction, therefore it is highly desirable to record methods that can boost the amount of data available for deep model training.

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