Open Access database of EEG signals recorded during imagined speech

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ABSTRACT

Brain-Computer Interfaces (BCI) that could decode thoughts into commands would improve the quality of life of patients who have lost control over voluntary muscles. Imagined speech consists in imagining the pronunciation of words, without moving or emitting sounds. In this study, we introduce a new open access database of *electroencephalogram* (EEG) signals recorded while 15 subjects imagined the pronunciation of two groups of Spanish words. The first one contained the vowels /*a*/, /*e*/, /*i*/, /*o*/, /*u*/; and the second one corresponds to the commands up, down, left, right, backward and forward. Each subject repeated each word 50 times in a random order, meanwhile EEG signals were recorded using a six channel acquisition system and sampled at 1024 Hz. For comparison, some blocks were recorded using the pronounced speech condition, in which audio and EEG signals were acquired simultaneously. The EEG signals were filtered for artifact's removal between 2 Hz and 40 Hz using a *finite impulse response* (FIR) pass-band filter. As a preliminary analysis of the EEG data, an offline classification method is presented. Accuracy rate is above chance level for almost all subjects, suggesting that EEG signals possess discriminative information about the imagined word.

Keywords: EEG, Database, Imagined Speech, Covert Speech, Classification

1. INTRODUCTION

Some severe muscular disorders, such as amyotrophic lateral sclerosis (ALS), advanced stages of multiple sclerosis, and brainstem stroke, among others, can make the usual pathways employed for communication unavailable. The patients suffering from these conditions found themselves in a locked-in state, because of lack of control over voluntary muscles. Even though their intellectual capabilities are intact, they cannot interact with their environment.[1,2]

Brain Computer Interfaces have been developed for the purpose of bringing a new communication path, allowing the use of brain signals to control devices, such as wheelchairs or voice synthesizers. Usually, the EEG is chosen as a measure of brain activity because it is a non-invasive technique, has a relative low cost when compared to others like *functional magnetic resonance imaging*, and it is portable due to the simple equipment needed for its acquisition system.[3]

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The aim of this work is to create an openly accessible database of EEG signals acquired during imagined and pronounced speech from healthy subjects. This would provide a starting point for future research about imagined speech and facilitate the development of new classification algorithms by avoiding the time-consuming stages of acquisition and artifact removal. Furthermore, we present the results achieved using a similar classification method as the one proposed by Torres-García et al. in Ref. 4, which uses *Relative Wavelet Energy* (RWE) to generate the feature vectors and *Random Forest* (RF) and *Support Vector Machines* (SVM) as classifiers. These results are intended to be used as an initial baseline reference for future works, but it is not the purpose of this study to find an optimal classification algorithm.

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This work is organized as follows. In Section 2 a brief description of the subjects selection process, the protocol implemented and the data collection methodology is presented. Section 3 introduces the feature extraction stage and the classifiers employed. The results obtained and a succinct discussion are presented in Section 4, followed by the conclusions of this work in Section 5.

2. MATERIALS AND METHODS

2.1 Subjects

The subjects in this study were fifteen young adults who voluntarily agreed to participate. All understood the anonymity of the data collected and gave informed consent to create a database using their EEG signals. The subjects were Argentinian college students, healthy and native Spanish speakers. The group included eight men and seven women, with a mean age of 25 years old. Only one of the subjects reported to be left-handed, while the rest were right-handed. Handedness is relevant because of the suspected relation with the language dominant hemisphere of the cerebral cortex.[5]

Also, given the relationship between hearing impairment and distorted speech development, an audiometry was performed on each subject to discard hearing pathologies that could introduce changes in speech, and thus possibly modify EEG patterns. The software used to perform the audiometries was designed by the University of New South Wales and is available online on its website*. The program measures the hearing sensitivity to different frequencies, described by a curve of equal loudness. None of the subjects presented moderate or severe hearing deficiencies so, for the purpose of this study, they can be considered normal listeners.

2.2 Experimental Protocol

To build the database, an ad-hoc protocol was defined to ensure that every subject was under the same conditions during the experiment. During the recording sessions, subjects seated in a comfortable chair at a distance of approximately one meter from an LCD display, where the target words were visually presented. Additionally, an auditory stimulus was heard through a pair of headphones indicating the intended word. In order to reduce intra-subject variance, the registers were collected during a single recording session for each subject.

Two groups of words have been selected as "dictionaries" for this study. The first one contains the Spanish vowels: /*a*/, /*e*/, /*i*/, /*o*/ and /*u*/, which were selected due to its acoustic stationarity, simplicity and lack of meaning by themselves. The second group also includes Spanish words, but in this case they correspond to possible commands, and were selected due to their direct association to the control of an external device in a BCI system. The command words were: "arriba", "abajo", "derecha", "izquierda", "adelante" and "atrás" (up, down, right, left, forward and backward, respectively).

EEG signals were recorded under two conditions: during imagined speech and pronounced speech, both modes being chosen to allow future studies towards identifying the EEG patterns that differentiate overt from covert speech. In imagined speech mode, only the EEG signals were registered while in pronounced speech audio signals were also recorded. The number of trials (repetitions, several in each block) performed by each subject for each word is 50, with forty corresponding to the imagined speech mode and the other ten belonging to the pronounced speech modality.

Target stimuli were presented in a sequence comprised of four intervals of predefined duration as shown in Figure 1. (i) A ready interval is presented first for 2 seconds, in which the subject is informed that the rest interval finished and a new cue would be displayed soon. (ii) Then the target word is presented, both visually and acoustically, during the stimulus presentation interval of 2 seconds. (iii) In the Imagine/Pronounce stage an image displays the task requested (either imagined or pronounced speech). It is in this stage that the subject has to imagine the pronunciation or pronounce the word given as cue. In the case that the word is a vowel, the subject must perform the task during the complete 4 seconds of this interval duration, while if the word is a command, a sequence of three audible clicks will indicate when to imagine or pronounce the target word. (iv) The rest interval consists of a 4-second period when the subject is allowed to move, swallow or blink. This last stage is necessary because in all the other stages these actions must be avoided to reduce the presence of artifacts in

*www.phys.unsw.edu.au/jw/hearing.html accessed August 20, 2016

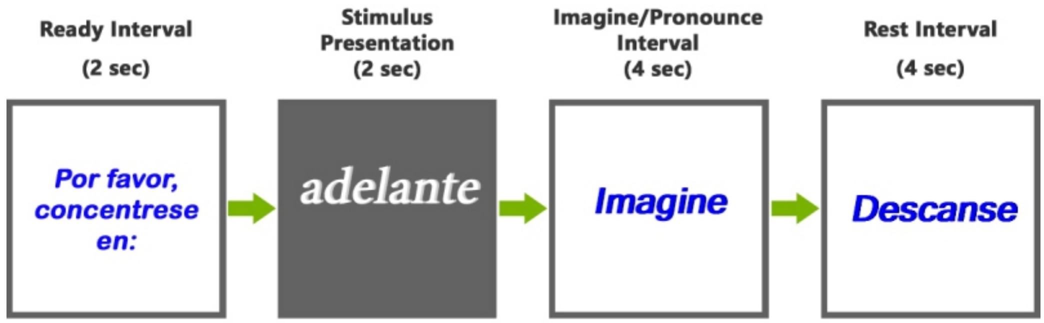


Figure 1. Sequence time course for the presentation of one stimulus, in this particular case for the word "adelante" and under the imagined mode. Also, the name and length of each interval are shown.

the recorded signals. Using fixed duration windows facilitates preprocessing and implementing feature extraction techniques.

To shorten the recording process, all the words of the selected dictionary were presented twice in each block in a random order, defining blocks of two different lengths. As a result, the blocks containing vowels as stimuli had a duration of 2 minutes and the blocks where command words were target lasted 2.43 minutes. Considering the long duration of the acquisition process, breaks were introduced to allow the subjects to relax and keep the focus during the recording process. In average the complete session, where at least fifty repetitions of every word of both groups were recorded, took 3.5 hours.

2.3 Data Collection

The recording sessions were performed in the offices of the *Laboratorio de Ingeniería en Rehabilitación e Investigaciones Neuromusculares y Sensoriales* (LIRINS) in the Faculty of Engineering of the National University of Entre Ríos (UNER). The offices were located in a quiet area, far from external noise sources and gathering places, in order to minimize distractions as well as improving the quality of the recorded audio signals. On arrival, the experimental protocol was described to the subjects, who proceeded to sign the informed consent document.

EEG signals were registered using Ag - AgCl cup electrodes, which were attached to the scalp with conductive paste and without using an electrode cap. Electrode positions were determined by measuring distances from standard head anatomical landmarks proposed by the 10-20 international system.[6] A referential montage was implemented using the electrodes placed over F3, F4, C3, C4, P3, and P4 as active electrodes, while reference and ground corresponded to the ones on the left and right mastoids, respectively (see Fig. 2). Electrode positions were selected to be as close as possible to the cortical areas related to language processing and described in the Geschwind Wernicke model,[7] but far enough from the muscles involved in speech to reduce the myoelectric noise acquired in the pronounced mode.

The acquisition system used to register EEG signals consisted of an 18-channel Grass® analog amplifier model 8-18-36 and a DataTranslation® analog-to-digital converter board model DT9816. The amplifier provides an analog band-pass filter for each channel, being the lower and upper cutoff frequencies set to 0.3 Hz and 35 Hz. The ADC board has only six simultaneously converted channels–not including ground and reference electrodes– limiting the number of recorded EEG channels. The EEG signals were sampled at a sampling rate of 1024 Hz with a 16-bit resolution and stored in a notebook hard drive.

A Shure® SM58 microphone was employed to register the pronounced speech, which has a frequency range adapted to vocals and a spherical filter that reduces breathing noise. Then, the acquired sound was amplified and digitized using an M-Audio® MobilePre preamplifier at a sampling rate of 44.1 kHz and with a resolution of 16 bits. In the same way as the EEG signals, the audio signals were saved in the hard drive of a notebook computer.

Both EEG and audio signals were collected using the software platform BCI2000 described by Schalk et al. in Ref. 8. BCI2000 is comprised of four modules: Operator, Source, Signal Processing, and User Application. A

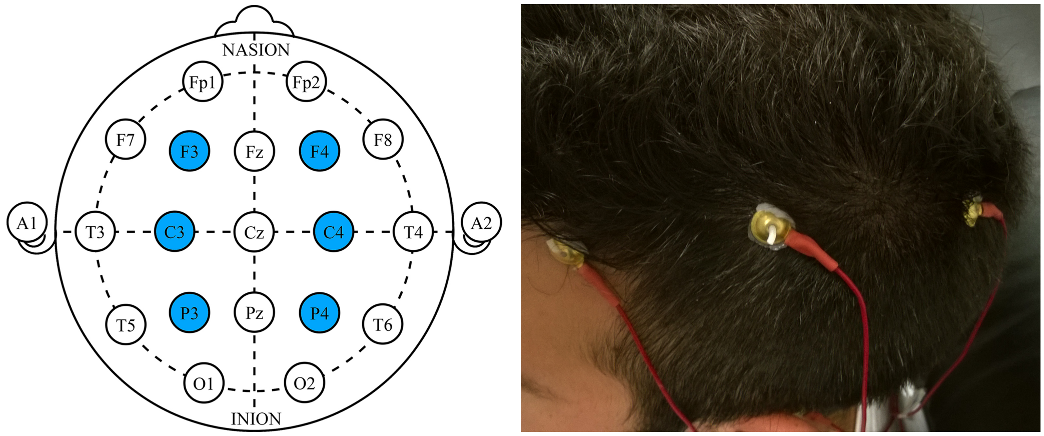


Figure 2. Electrode distribution for the EEG registers.

new User Application module, called ImaginedSpeech, was created using VisualStudio 2010 Express Edition to implement the protocol defined in Section 2.2. This application allowed users (the supervisor of the experiment, in this case) to define the length of every interval and to specify the images that were shown in each of them. Also, it was possible to indicate the modality and the group of words shown for a block, with the supervisor in charge of selecting the desired combination of this two parameters at runtime.

After the recording session was completed, the EEG signals were visually scrutinized searching for artifacts. Those registers that contained artifacts within the Imagine/Pronounce interval, such as muscular, electrode pop or saturation artifacts, were marked to be eliminated because they tend to obscure the underlying EEG pattern or are difficult to remove. Instead, the ones presenting blinking artifacts were identified but not erased, due to the existence of some techniques such as *Independent Component Analysis* (ICA), that separate the artifacts from the signal of interest.[9]

The EEG signals preprocessing stage consisted of using a 2 Hz to 40 Hz digital band-pass filter implemented with a low-pass and a high-pass FIR filters of orders 372 and 1204, respectively. The selection of FIR filters is based on the fact that minimal distortion is introduced by its linear phase and constant group delay. The 788-sample group delay produced by the FIR filters was compensated by left-shifting without any signal loss. The low-pass filter attenuated the line noise at 50 Hz by 60 dB, therefore a notch filter was not required. A fourth order Butterworth low-pass filter with a cutoff frequency of 10 kHz was used to filter the voice signals.

The filtered registers were sectioned, leaving only the signals captured during the Imagine/Pronounce interval. Then, the six EEG signals corresponding to channels F3, F4, C3, C4, P3, and P4 of one stimulus repetition were concatenated in a vector following that order. In the final positions of the vector, three labels were added specifying the mode, the stimulus code and the presence of blinking artifacts. A matrix was created in which each row represented the EEG signals recorded during a particular Imagine/Pronounced interval. A similar procedure was applied to create the matrix containing the audio recordings, except that only two labels were appended to the vector containing the single-channel voice signal. The first label indicated the stimulus, and the second one indicated the row of the EEG matrix where the simultaneously acquired EEG signals were stored. For each subject, both matrices were saved in separate Matlab® files and stored together with a plain text file containing the subject's disclosable information.

3. DATA ANALYSIS AND CLASSIFICATION

In this section, the steps of a preliminary analysis of the EEG signals collected in the database are described. Only the signals recorded using the imagined speech modality were used, and imagined vowels and commands were processed separately.

3.1 Feature Extraction

Considering that EEG signals are non-stationary and the spectral content varies temporally and spatially, a multiresolution approach was used. The Wavelet Transform decomposes a signal using a set of functions called wavelets, which are scaled and shifted versions of another function named mother wavelet $\psi(t)$. Then, the wavelet dictionary could be expressed as:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), \tag{1}$$

where $a, b \in \mathbb{R}$, with $a \neq 0$, are the scale and shifting factors, respectively. But when those parameters are selected at discrete steps based on powers of two, the *Discrete Wavelet Transform* (DWT) of the function $f(t)$ can be written as:

$$DWT_{\psi}(j,k) = \int_{-\infty}^{\infty} f(t)\psi^*_{j,k}(t)dt, \tag{2}$$

where $\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\psi\left(2^{-j}t - k\right)$. An efficient implementation for the DWT was proposed by Mallat in Ref. 10, using an algorithm based on successive convolutions with quadrature mirror filters. In each level, the signal is decomposed in approximation and detail coefficients, and then the approximation signal is downsampled by a factor of 2. The process repeats itself until reaching the desired number of decomposition levels.

The feature extraction process started with downsampling eight times the EEG signals corresponding to the imagined modality, obtaining an effective sampling rate of 128 Hz and thus reducing the amount of data to be processed. After that, the DWT with five levels of decomposition was computed for each EEG channel, selecting the mother wavelets from the Daubechies family. Four orders of Daubechies–2, 4, 6, and 8–were used to search for correlations between the order and the achieved recognition rate. An example of the decomposition levels of an EEG signal for one channel is shown in Figure 3.

Being $d_{i,j}$ and $a_{i,j}$ the j-th detail and approximation coefficients corresponding to the decomposition level i, the energy of the i-th resolution level E_i, can be expressed as:

$$E_i = \begin{cases} \sum_j |d_{i,j}|^2, & \text{for } i \leq N. \\ \sum_j |a_{i,j}|^2, & \text{otherwise.} \end{cases} \tag{3}$$

where N is the number of decomposition levels.

If we define the total energy of all the decomposition as $E_T = \sum_i E_i$, we can use it to compute the Relative Wavelet Energy (RWE) for each decomposition level i as:

$$\text{RWE}_i = \frac{E_i}{E_T}, \qquad \text{with } i = 1 \ldots N+1, \tag{4}$$

In accordance with the 128 Hz sampling frequency, the six decomposition levels correspond to the following frequency bands: 32-64 (D1, γ); 16-32 (D2, β); 8-16 (D3, α); 4-8 (D4, θ); 2-4 (D5, δ) and <2 (A5). Since the frequency band of D1 is associated with myoelectric noise, that decomposition level was not used to calculate the RWE. The feature vector was formed with the RWE of the decomposition levels D2 to D5 and A5 of each of the six EEG channels, hence each instance was described with a thirty-element vector.

3.2 Classification

In this preliminary analysis, the feature vectors of the EEG signals were classified using two types of classifiers, a Support Vector Machine (SVM) and a Random Forest (RF) algorithm. The SVMs are classifiers that find an hyper-plane within the features space, maximizing the margin between the nearest data point of each class and the hyper-plane. Despite being originally designed for binary classification problems,[11] the SVMs can be extended to multiclass problems. In this study, a "one vs one" reduction was used to tackle the multiclass problem. SVM with linear kernels were used and different C complexity values were tested. RF is a collection of

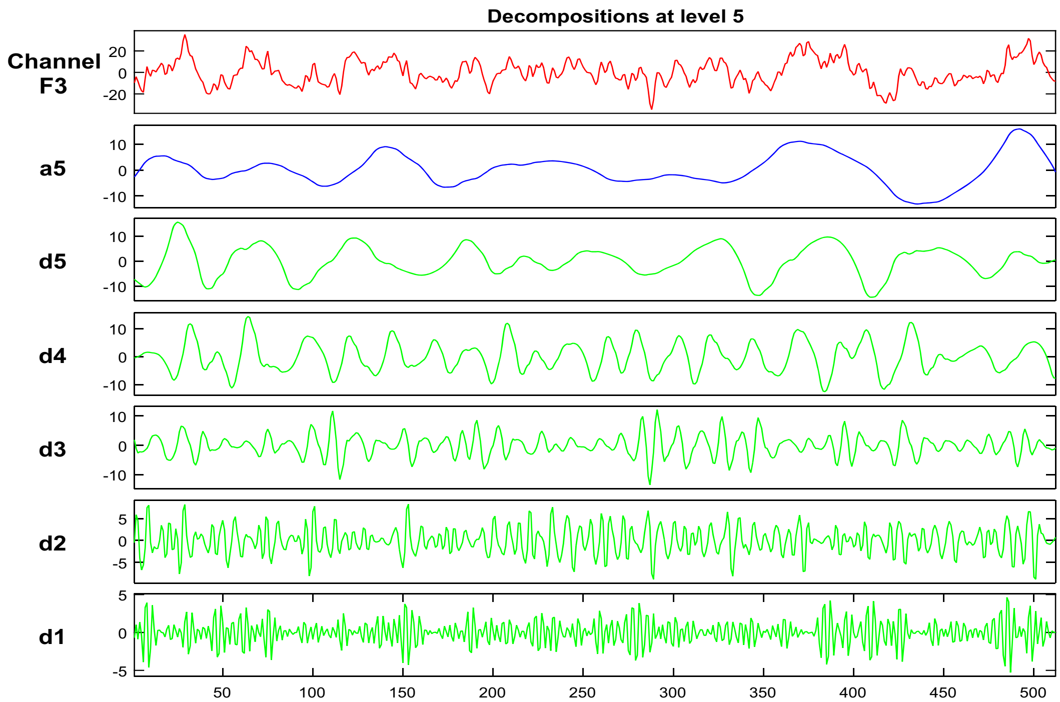


Figure 3. A 4-second EEG signal recorded from channel F3 and downsampled to 128Hz, and its five-level DWT decomposition using a 4th order Daubechies wavelet.

tree-based classifiers, where each tree is built using a randomly selected group of features, independently sampled with an identical distribution for all trees.[12] For each feature vector, each tree predicts a class and the output is the class having the majority of votes. RFs were built using 4, 5 and 6 features randomly selected at each node, and RFs made of 10, 50, 100, 200, and 500 trees were tested.

The implementations used for both classifiers are the ones provided by Weka*, a workbench containing machine learning algorithms and feature visualization tools. The classifiers performance was measured by its accuracy, which can be expressed as the ratio of the number of instances correctly classified and the total number of instances. The accuracy that was reported was the mean of ten repetitions of a 10-fold cross-validation system using different seed values.

4. RESULTS AND DISCUSSION

Over the course of two months, EEG and audio signals of fifteen subjects were acquired employing the proposed protocol and for almost all subjects the fifty-repetition per stimulus condition was fulfilled. Then, a folder structured database was built with the recorded signals in which the root folder contains a plain text file describing the protocol, another plain text file with the number of recordings per subject, stimulus and modality, and a folder for each subject. The folders of all the subjects consist of three files, two representing the .mat extension files in which the audio and EEG signals were stored, and a plain text file in which the disclosable information of the subject is documented (see Figure 4).

This type of database was selected because it is the typical structure used for storing biomedical signals and allows the addition of new sets of data without needing to restructure the database. The database final version is made of 15 folders and 47 files, with a total weight of 2.48 Gb. It contains 4201 recordings using vowels as

*http://www.cs.waikato.ac.nz/ml/weka/ accessed August 20, 2016

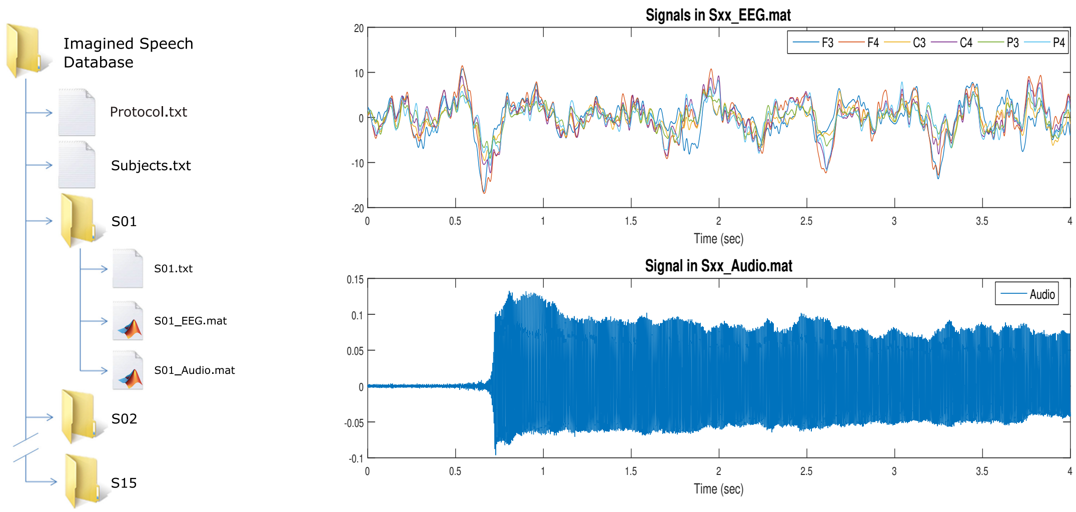


Figure 4. Folder structure of the database and an example of the signals found in the EEG and Audio files.

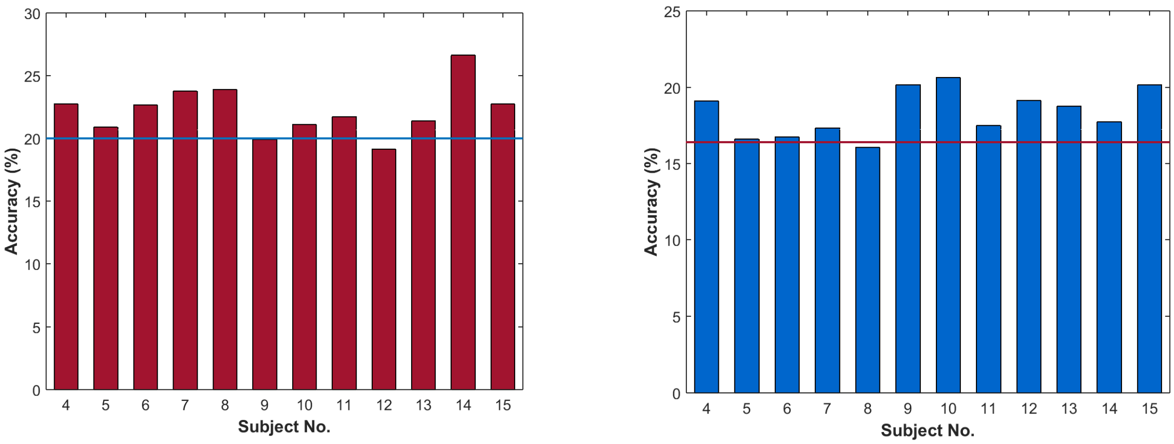
Table 1. Recognition rates for the two groups of stimuli achieved for subjects S01 to S03.

Subject	Commands		Vowels	
	RF	SVM	RF	SVM
S01	**19.31**	17.26	**23.68**	22.35
S02	19.58	**19.81**	**22.52**	22.01
S03	**19.92**	17.72	**21.96**	21.45
Mean	**19.60**	18.26	**22.72**	21.94

stimulus and 5113 recordings in which command words were presented. Considering that each recording lasts 4 seconds, the total recording duration was 37,256 seconds of six-channel EEG signals (approximately 10.3 hours) and 7,892 seconds of single-channel audio (approximately 2.2 hours). The database is stored in the *Research Institute for Signals, Systems and Computational Intelligence* (**sinc**(*i*)) server and was made publicly available at http://fich.unl.edu.ar/sinc/downloads/imagined_speech/. Additional details about the material and experimental conditions for each register can be found in the Appendix A.

A preliminary experiment was performed with the EEG signals recorded during imagined speech. Recordings belonging to subjects S1, S2 and S3 were used to find the best configuration for the SVM and RF classifiers, and then the best classifier was employed for the remaining subjects. Also, Daubechies of different orders were tried as mother Wavelet, but no significant difference was detected. Therefore, fourth order Daubechies (db4) were used to achieve the following results. An RF with 200 trees that used 5 random features and an SVM with a complexity coefficient of 0.9, yielded the best results for the command word dictionary. Thus, the same configuration was applied for the vowel dictionary. The recognition rate for the first 3 subjects is shown in Table 1.

Given that a better result was obtained using the Random Forest algorithm for the two groups of stimuli than with the linear SVM, the first one was used to process the EEG signals of the rest of the subjects. The mean accuracy after ten iterations with different seeds for subjects S4 to S15 for the command words and vowel group is depicted in Figure 5. The mean recognition rate for all the subjects was 22.32 (±1.81) for the vowels and 18.58 (±1.47) for the words that express commands. So the mean accuracy is greater than chance for almost all the subjects in both groups (being the chance level 20% and 16.6% for the vowel and command groups, respectively). The results are worst than those obtained in Ref.4 but better than the ones reported in Ref.13. However, in Ref.4 the different stimuli are not presented in random order, as it is the case in both Ref.13 and this work. The randomization of the stimuli presentation increases the difficulty of the task, since it prevents other features that are not related with the imagery speech task from aiding the classification process.[14] The classification accuracy could be improved using more information besides the basic spectral one employed in this



(a) Vowel Recognition Accuracy

(b) Command Recognition Accuracy

Figure 5. Accuracy percentage achieved for subjects S04 to S15 using a Random Forest algorithm for both groups of words: vowels and commands. Chance level is indicated by a horizontal line, at 20% and 16.6%, respectively.

initial approach. The addition of other temporal features such as mean and standard deviation of each channel, should be explored.

5. CONCLUSIONS

The acquisition process of EEG signals requires specific equipment and time, and this coupled with the fact that there are not public databases of EEG recordings during imagined speech, hamper the number of investigations regarding the classification of imagined words. In this work, a public database of EEG signals recorded while the subjects imagined or pronounced two groups of words or vowels was presented. It is believed that this will facilitate and encourage studies tending to improve the recognition rates for imagined words, and ultimately lead to the development of BCI systems that could decode thoughts.

The results of an exploratory experiment were described in this work, using as features the Relative Wavelet Energy of each channel and five levels of decomposition. In addition, two classifiers were tested, being Random Forest the best. The accuracy achieved is above chance level suggesting that there is information of the imagined word within the EEG signal, although further research must be done to find the features that provide better discriminative information and the optimal classifier.

6. ACKNOWLEDGEMENTS

This work was supported in part by the Consejo Nacional de Investigaciones Científicas y Técnicas, CONICET, through PIP 2014-2016 No. 11220130100216-CO, and by the Universidad Nacional del Litoral, UNL, through CAID-UNL 2011 Project No. 525 within PACT "Señales, Sistemas e Inteligencia Computacional".

APPENDIX A.

In this appendix, additional information regarding the subjects and the recordings contained in the database are presented. Table 2 shows the personal information collected prior to the recordings for each subject. In Tables 3 and 4, the number of trials recorded from each subject, identified by modality and stimulus, are indicated for the dictionary of vowels and commands, respectively.

Table 2. Disclosable personal information of the subjects.

ID	**Gender**	**Age**	**Handedness**	**Nationality**	**Province**
S01	Female	24	Right	Argentina	Entre Ríos
S02	Female	28	Right	Argentina	San Luis
S03	Female	24	Right	Argentina	Entre Ríos
S04	Male	25	Right	Argentina	Tierra del Fuego
S05	Female	24	Left	Argentina	Entre Ríos
S06	Male	25	Right	Argentina	Entre Ríos
S07	Male	25	Right	Argentina	Neuquén
S08	Male	25	Right	Argentina	Santa Fe
S09	Male	24	Right	Argentina	Buenos Aires
S10	Male	26	Right	Argentina	Buenos Aires
S11	Female	25	Right	Argentina	Entre Ríos
S12	Male	28	Right	Argentina	Santa Fe
S13	Female	25	Right	Argentina	Entre Ríos
S14	Male	25	Right	Argentina	Entre Ríos
S15	Female	24	Right	Argentina	Entre Ríos

Table 3. Number of trials recorded by subject and modality using as stimuli the vowels group (I:Imagined speech / P: Pronounced speech).

ID	***/a/***		***/e/***		***/i/***		***/o/***		***/u/***		**Total**
	I	P	I	P	I	P	I	P	I	P	
S01	56	14	53	10	55	12	55	10	55	10	**330**
S02	44	12	44	12	44	12	44	12	44	12	**280**
S03	42	13	44	12	44	13	44	14	42	13	**281**
S04	41	11	43	12	43	12	41	11	41	11	**266**
S05	43	11	43	11	44	9	42	9	43	12	**267**
S06	43	12	43	12	38	12	43	11	44	12	**270**
S07	44	12	37	11	38	12	39	12	42	10	**257**
S08	44	12	42	12	44	12	43	11	45	12	**277**
S09	49	11	48	12	48	14	47	13	48	13	**303**
S10	44	14	42	14	44	14	42	13	43	14	**284**
S11	43	12	44	12	43	12	44	12	44	12	**278**
S12	44	12	44	11	43	12	44	11	44	11	**276**
S13	44	11	43	10	43	12	43	12	44	12	**274**
S14	46	11	46	11	46	11	46	12	45	11	**285**
S15	45	11	44	11	45	12	38	12	43	12	**273**
Total	**672**	**179**	**660**	**173**	**662**	**181**	**655**	**175**	**667**	**177**	**4201**

Table 4. Number of trials recorded by subject and modality using as stimuli the commands group (I:Imagined speech / P: Pronounced speech).

ID	"arriba"		"abajo"		"adelante"		"atrás"		"derecha"		"izquierda"		Total
	I	P	I	P	I	P	I	P	I	P	I	P	
S01	51	11	51	10	51	7	51	9	51	7	49	9	**357**
S02	43	11	44	11	44	12	43	12	43	12	44	12	**331**
S03	46	13	47	14	48	13	45	14	47	14	45	14	**360**
S04	44	10	43	13	42	13	45	13	43	13	46	12	**337**
S05	41	12	39	8	41	12	42	9	40	11	39	12	**306**
S06	44	13	39	13	44	14	44	14	44	14	41	13	**337**
S07	41	12	41	14	43	11	43	13	41	13	43	12	**327**
S08	46	13	47	13	47	14	44	14	47	12	47	13	**357**
S09	46	12	45	12	46	12	45	12	43	12	45	12	**342**
S10	45	14	46	14	45	12	43	11	46	14	43	14	**347**
S11	47	12	47	12	45	12	47	12	46	12	46	12	**350**
S12	45	11	46	11	45	11	46	11	45	10	45	12	**338**
S13	43	13	43	14	44	14	45	14	46	14	43	14	**347**
S14	48	12	48	12	47	12	48	11	48	11	45	12	**354**
S15	45	11	42	12	43	11	41	12	44	11	40	11	**323**
Total	**675**	**180**	**668**	**183**	**675**	**180**	**672**	**181**	**674**	**180**	**661**	**184**	**5113**

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