Euclidean distance as functional connectivity measured obtained from EEG data applied to individual recognition: a viability study

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Abstract— The use of electroencephalography (EEG) signals for biometric purposes has gained attention in recent years, and many works have shown that it is possible to identify a person based on features extracted from these signals. In this work, the Euclidean distance was used as a measure of functional connectivity for the classification of resting-state EEG signals from 30 volunteers. The analysis was done by slicing the signals of two acquisitions for each subject, one with eyes open (A1) and another with eyes closed (A2), in epochs of 1 second each, one from the tenth second of the signal (E1) and another from the second before last (E2). From there, we constructed connectivity vectors, which were then compared with each other. To do this, the Euclidean distance was also used, and three tables were obtained: A1-E1 compared to A1-E2; A1-E1 compared to A2-E1; A1-E1 compared to A2-E2. With the favorable result being the smallest distance belonging to vectors of the same individual, the obtained accuracies were 87%, 27%, and 30%, respectively, a result that can be improved with more sophisticated connectivity and comparison methods.

I. Introduction

A. Electroencephalography

Electroencephalography derives from the Greek words enkephalo (brain) and graphein (to write), and consists of the record of the electric signal generated by the cooperative action of brain cells. It was first described by Hans Berger in the late 1920s, when he recorded signals that fluctuated rhythmically when the eyes were shut, but which became far less rhythmic and of generally smaller amplitude when the eyes were open. Electroencephalography data is acquired by electrodes placed in the scalp of the individual, usually in a helmet positioning system, which record the time course of extracellular field potentials generated by the synchronous action of neurons and glial cells.

An analogy from Professor Andrea Biasiucci helps understand the characteristics of the signals obtained with EEG. Imagine you are a journalist equipped with a hand-held microphone, which will here be analogous to a recording electrode, more specifically a patch clamp. You are reporting from a soccer match. If you are standing next to the coach, you can interview her and comprehend her voice despite the noise throughout the stadium. This is analogous to recording action potentials of individual neurons. If you are in the press box, you will not be able to record the ongoing conversations between the coach and players on the field, but instead can capture the general commentary of other reporters inside the press box as well as the hum of the audience outside. This is analogous to recording local field potentials, where there are contributions of both proximal and relatively distal events, measured by invasive electrodes. Finally, from your hotel balcony, having lost your press credentials, you may nonetheless be able to hear the joyful cry in unison of the team's supporters from within the stadium when a goal is scored. This is analogous to EEG recordings, with non invasive electrodes, placed in the scalp.

Electroencephalography (EEG) is one of the most widely used techniques in the analysis of brain activity nowadays [1]. This is mainly due to its relatively lower cost, portability, and high temporal resolution (mi~~of the order of mil~~liseconds), in comparison with other neuroimaging techniques. It plays a prominent role in the diagnosis of different neurological diseases, such as epilepsy [2]. The analysis of seizures evolution in epilepsy patients is used for their classification, which offers the possibility of an application of appropriate treatment [3] [4]. In the pharmacy industry, EEG is used to obtain drug profiles. The method relies on estimation of spectral power in basic frequency bands before and after drug application and finding the significance of changes by means of statistical tests.

An interesting possible future application for electroencephalography is the detection of pain in intubated and unconscious patients. It is based on the pain center in the brain cortex, where pain stimuli from the entire body are processed and could be detected in EEG analysis. However, the determination of geometry and orientation of cortical sources of EEG is a complex problem. Electrical activity propagates along neuronal tracts and by volume conduction. Potentials measured by scalp electrodes are attenuated by media of different conductivity and complicated geometry (cerebrospinal fluid, skull, skin), which results in a decrease of their amplitude by over an order of magnitude. However, the major problem in localization of the sources of EEG activity stems from the fact that different configurations of sources can generate the same distribution of potentials on the scalp.

B. EEG and Biometry

More recently, the idea of using EEG to distin~~nals to distin~~guish individuals, i.e., using them for biometric purposes, has been investigated by several works [5][6][7]. The goal is mainly user recognition in security systems [8], since EEG provides signals obtained exclusively from living organisms and, moreover, these signals vary according to different types of stimuli or tasks. One of the most investigated paradigm options is actually the absence of stimuli or tasks, i.e., the use of EEG signals obtained in the resting state [9][10], which can be achieved by any type of individual, simplifying difficulties arising from potential motor or cognitive impairments, besides decreasing the incidence of motion artifacts in the obtained signals due to immobility during acquisition. In addition, biometric information can be extracted from specific electrodes, or also from the relationship between the EEG signals obtained at different electrodes. This latter method is known as brain connectivity.

C. Brain Connectivity

Neurons and neural populations do not function as islands onto themselves. Rather, they interact with other such elements through their afferent and efferent connections in an orchestrated manner so as to enable different sensorimotor and cognitive tasks to be performed. The concept of brain connectivity is the core of neuroscience and of the notion of brain and intelligence itself. It is based on the idea that different brain regions act together to perform sensory, motor, and cognitive tasks, forming brain networks. Thus, studying the interaction patterns between these signals can provide information that is relevant and possibly specific to the individual.

The types of brain connectivity analysis are three. They consist of three different possibilities for the nature of interaction: it can derive from anatomical links, found in the arrangement of individual synaptic connections between morphologically and physiologically distinct neuronal types; from causal interactions (called effective connectivity), which describes networks of directional effects of one neural element over another, usually inferred through the application of time series causality measures such as Granger causality; or from statistical dependencies, known as functional connectivity [11]. The latter is calculated by comparing the activity of pairs of brain regions using some measure of similarity [12].

Previous studies have explored different similarity measures for biometrics ends: the first studies in the area [13][14] proposed the use of spectral decomposition as a feature for identifying individuals, and obtained an accuracy of almost 90% [14]. Since then, other methods have been applied, some combinations reaching up to 100% accuracy, such as the use of correlations between event-related potentials (ERPs) [15] induced by a rapid serial visual presentation (RSVP) [16] and the use of spectral coherence (COH) [9] of the resting state with eyes open and closed. However, the effects of increasing the number of subjects in the study, and changes in the gender and age of the participants are discussed in [17], in which the authors point out that the accuracy rates found are strongly dependent on specific and restricted parameters. Therefore, more research, with a greater diversity of methods and study groups, is needed. Besides these already tested methods, one can also mention Spearman's correlation applied to the Hilbert transform of time series [18], the phase-locking value [19], the imaginary part of the phase-locking value [20], the phase lag index [21], and mutual information applied to ordinal patterns [22] as possibilities for further research in the area.

The present work aims to use functional connectivity measures obtained with the Euclidean distance calculation method, based on resting-state EEG data, and explore the viability of using the resulting brain networks for biometric purposes.

II. Materials and Methods

To perform the present work, a database (described in Section A) containing two acquisitions for each individual was chosen. The data were initially pre-processed to eliminate noise and artifacts (Section B). Subsequently, two epochs were chosen from each acquisition, and from these, connectivity matrices were calculated (Section C). Lastly, the connectivity matrices were compared across individuals, as detailed in Section D.

A. Data acquisition

The data used were obtained from the online database "EEG Motor Movement/Imagery Dataset" (https://physionet.org/content/eegmmidb/1.0.0/) [23], from the BCI R&D Program, Wadsworth Center, New York State Department of Health. The database has data from 109 volunteers, with 14 acquisitions each: two of one-minute duration at rest (one with eyes open, one with eyes closed), and another 12 of two-minute duration in which the volunteer performed specific tasks, with three acquisitions for each task. EEG data were acquired using BCI2000 software (http://www.bci2000.org) [24], which synchronizes EEG with other biosignals and input devices, in a 64-electrode array in the international 10-10 system [25] (Figure 1), with a sampling rate of 160 Hz. In the present work, the first two acquisitions of 30 of 109 subjects, arbitrarily selected, were used. Hereon, the eyes open acquisition is referenced as A1 and the closed eyes acquisition as A2.

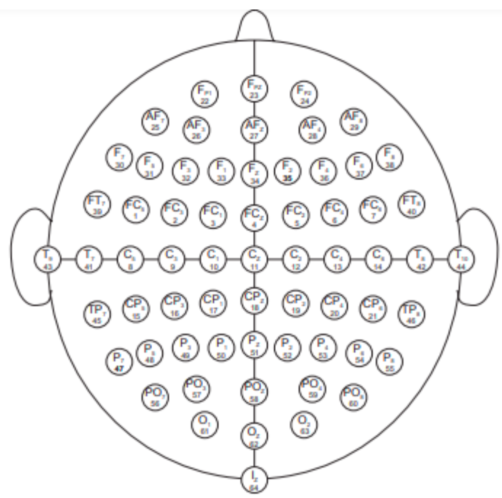

Fig. 1: International 10-10 electrode montage system. Obtained from: https://physionet.org/content/eegmmidb/1.0.0/64_channel_sharbrough.pdf

B. Pre-processing

For data pre-processing, the software EEGLAB [26] was used, on the MATLAB platform (2018, Natick, Massachusetts: The MathWorks Inc). The first step was to remove artifacts by visual inspection through graphical plotting, discarding whole channels in the case of noise indicating malfunctioning electrodes, in order to retain only signals containing usable brain activity. An independent component analysis (ICA) [27] decomposition was also performed, to remove eye blinks and muscle activity of the subject, using the ICLabel extension.

Using the Basic FIR Filter tool, the signals were bandpass filtered between 4 and 50 Hz. Through the same technique, the α frequency band (8-12 Hz) was eliminated from the acquisition files. A peak in this band is characteristic of the closed-eye state and common to all individuals [28], and would therefore interfere with the results without presenting a biometric potential. The EEG data was then re-referenced to the average of all electrodes by the common average referencing (CAR) [29] method to remove common artifacts, and then the signals had the 60 Hz frequency removed using the CleanLine tool, which is the power supply frequency in the United States, where the measurements were taken.

C. Functional Connectivity Matrices

Two 1 second epochs were extracted from both acquisitions of each subject. The first epoch was the tenth second of the signal, which we are referring as E1, and the latter was the penultimate second, referred as E2. Then, connectivity matrices were computed for both epochs from all 30 subjects through the method of Euclidean distance, detailed in the following.

The Euclidean distance in a series of two electrodes can be calculated in order to analyze how similar the signals are. Mathematically, the distance between the series of electrodes i and j can be calculated by

$$d(i,j) = \sqrt{\sum_{k=1}^{L} (i_k - j_k)^2}$$

where L is the series length according to the sampling rate of 160 Hz and epoch duration of 1 second (Appendix A).

With this formula, an $n \times n$ matrix is obtained, where n is the number of electrodes used in the data acquisition (in this case $n = 64$), wherein each element of the matrix is the distance between the row electrode and the column electrode. These matrices were then converted into 4096×1 feature vectors.

D. Comparison by Euclidean distance

To assess the similarity among signals, the Euclidean distance was also used. This was calculated between pairs of feature vectors of all subjects by the expression

$$D_{vw} = \|\vec{v} - \vec{w}\|_2$$

where v and w are the vectors being compared (Appendix B). Three combinations were made, as demonstrated in the flowchart (Fig. 2): A1-E1 X A1-E2; A1-E1 X A2-E1; A1-E1 X A2-E2 (Appendix C). If the minimum distance value was for vectors of the same individual, the result was favorable and the person was identified.

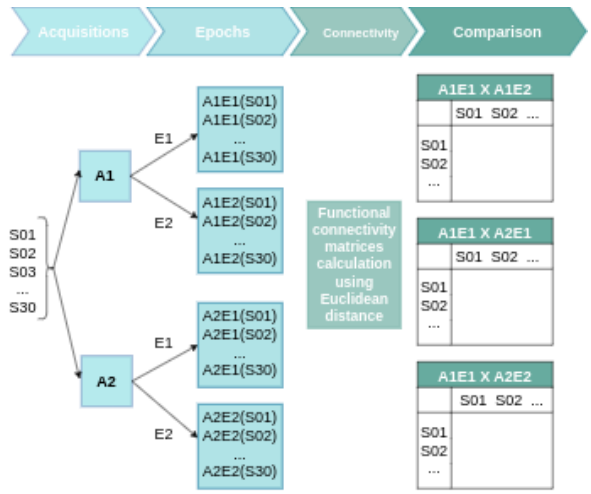

Fig. 2: Comparisons made in this work. In the flowchart, A1 stands for open eyes; A2 for closed eyes; E1 for the tenth second epoch; E2 for the second before last epoch.

III. RESULTS AND DISCUSSION

The accuracy values obtained for subject identification are displayed in Table 1, for each of the comparison combinations.

Table 1: Subject identification accuracies for all combinations of acquisition type and epoch.

A1E1 X A1E2	A1E1 X A2E1	A1E1 X A2E2
87%	27%	30%

The results show that comparing epochs obtained from the same acquisition was much better at identifying the subjects, with an accuracy of 87%, against accuracies of 27% and 30% obtained when comparing epochs obtained from different acquisitions. We expected that the comparison among signals from the same acquisition would result in better accuracy, but still, our assumption was that functional connectivity would be able to grasp information about electrode signals relationship that might be less variable among acquisitions, resulting in better accuracies than those achieved.

It may be that the Euclidean distance is not adequately capturing these relationships. Other methods could be used in the functional connectivity analysis, some that quantify oscillatory interactions or methods based on rigorous statistical theory of stochastic processes, such as coherence and Granger causality. Also, the comparison among epoch connectivity matrices was also performed using the Euclidean distance. Likewise, there are several other more sophisticated methods that could be applied for this comparison, beginning with the still simple Pearson's correlation coefficient [30] and ending with different types of machine learning classifiers such as linear discriminant analysis or support vector machines [31].

Relevant limitations of this work were the number of subjects whose EEG signals were used in our analysis and some characteristics of the pre-processing of the data. The first step of this process was a visual removal of artifacts, which is subjective and may have been inconstant through all the files.

IV. CONCLUSIONS

The approach proposed here had the intention to study the Euclidean distance as a connectivity measure for EEG-based biometry, using Euclidean distance also for comparison, analyzing its performance. Although results from same subject epochs were high, comparison between different subjects remained below from what would be considered accurate, therefore not being possible to identify individuals.

A first modification in the continuation of this work will be to include a larger number of subjects, which can make the results more reproducible and reliable. Other improvements include the use of more robust classification methods, such as Pearson's correlation coefficient, and the use of an automatic artifact removal algorithm in the pre-processing, like SOUND [32], eliminating the subjectivity of visual inspection. Finally, once we are able to increase subjects' sample, graph parameters could be extracted from the connectivity matrices and used instead of the actual connections.

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APPENDIX A

```
sujeito = 'S01';
modo = 'open';
%modo = 'close';

fs = 160; % sample frequency = 160 Hz
% com EEGlab, ler sinal correspondente a aquisição
E = double(EEG.data); % dados
Med = mean(E);
E = E-Med; % aplicação do CAR

n = size(E,1); % número de eletrodos
t0 = size(E,2); % # amostras temp open
t1 = 9*fs; % instante inicial (em amostras) do 1o trecho
t2 = t0-2*fs; % instante inicial (em amostras) do 2o trecho

d1 = zeros(n); % mat conn 10o s x 10o s
d2 = zeros(n); % mat conn penúltimo s  x penúltimo s
for j=1:n % loop sobre os eletrodos
  for i=1:n  % loop sobre os eletrodos
      for t=1:fs % número de amostras em 1 s
       d1(i,j)=d1(i,j)+(E(i,t1+t)-E(j,t1+t))^2;
       d2(i,j)=d2(i,j)+(E(i,t2+t)-E(j,t2+t))^2;
      end
  end
end

disp(d1) % matriz conn p/ 10o s
disp(d2) % matriz conn p/ penúltimo s

filename = [sujeito '_' modo '_10.mat'];
save(filename,d1);
filename = [sujeito '_' modo '_pen.mat'];
save(filename,d2);
```

APPENDIX B

```
% path para a pasta dos arquivos open
folder_open = '/home/evandro/VersãoFinalVetoresR01';
% path para a pasta dos arquivos close
folder_close = '/home/evandro/VersãoFinalVetoresR02';
% lista de arquivos das aquisicoes com olhos abertos 10o segundo
file_open_10 = {'S02_open_penVETORf.mat' ...
'S05_open_penVETORf.mat' ...
```

```
'S07_open_penVETORf.mat' ...
'S10_open_penVETORf.mat' ...
'S11_open_penVETORf.mat' ...
'S13_open_penVETORf.mat' ...
'S14_open_penVETORf.mat' ...
'S15_open_penVETORf.mat' ...
'S20_open_penVETORf.mat' ...
'S25_open_penVETORf.mat' ...
'S26_open_penVETORf.mat' ...
'S27_open_penVETORf.mat' ...
'S28_open_penVETORf.mat' ...
'S29_open_penVETORf.mat' ...
'S31_open_penVETORf.mat' ...
'S32_open_penVETORf.mat' ...
'S33_open_penVETORf.mat' ...
'S34_open_penVETORf.mat' ...
'S35_open_penVETORf.mat' ...
'S36_open_penVETORf.mat' ...
'S37_open_penVETORf.mat' ...
'S38_open_penVETORf.mat' ...
'S40_open_penVETORf.mat' ...
'S44_open_penVETORf.mat' ...
'S45_open_penVETORf.mat' ...
'S46_open_penVETORf.mat' ...
'S48_open_penVETORf.mat' ...
'S51_open_penVETORf.mat' ...
'S55_open_penVETORf.mat' ...
'S57_open_penVETORf.mat' };
% lista de arquivos olhos abertos penúltimo segundo
file_open_pen = {'S02_open_penVETORf.mat' ...
'S05_open_penVETORf.mat' ...
'S07_open_penVETORf.mat' ...
'S10_open_penVETORf.mat' ...
'S11_open_penVETORf.mat' ...
'S13_open_penVETORf.mat' ...
'S14_open_penVETORf.mat' ...
'S15_open_penVETORf.mat' ...
'S20_open_penVETORf.mat' ...
'S25_open_penVETORf.mat' ...
'S26_open_penVETORf.mat' ...
'S27_open_penVETORf.mat' ...
'S28_open_penVETORf.mat' ...
'S29_open_penVETORf.mat' ...
'S31_open_penVETORf.mat' ...
'S32_open_penVETORf.mat' ...
'S33_open_penVETORf.mat' ...
'S34_open_penVETORf.mat' ...
'S35_open_penVETORf.mat' ...
'S36_open_penVETORf.mat' ...
```

```
'S37_open_penVETORf.mat' ...
'S38_open_penVETORf.mat' ...
'S40_open_penVETORf.mat' ...
'S44_open_penVETORf.mat' ...
'S45_open_penVETORf.mat' ...
'S46_open_penVETORf.mat' ...
'S48_open_penVETORf.mat' ...
'S51_open_penVETORf.mat' ...
'S55_open_penVETORf.mat' ...
'S57_open_penVETORf.mat'};
% lista de arquivos das aquisicoes com olhos fechados penúltimo segundo
file_close_pen = {'S02_close_penVETORf.mat' ...
'S05_close_penVETORf.mat' ...
'S07_close_penVETORf.mat' ...
'S10_close_penVETORf.mat' ...
'S11_close_penVETORf.mat' ...
'S13_close_penVETORf.mat' ...
'S14_close_penVETORf.mat' ...
'S15_close_penVETORf.mat' ...
'S20_close_penVETORf.mat' ...
'S25_close_penVETORf.mat' ...
'S26_close_penVETORf.mat' ...
'S27_close_penVETORf.mat' ...
'S28_close_penVETORf.mat' ...
'S29_close_penVETORf.mat' ...
'S31_close_penVETORf.mat' ...
'S32_close_penVETORf.mat' ...
'S33_close_penVETORf.mat' ...
'S34_close_penVETORf.mat' ...
'S35_close_penVETORf.mat' ...
'S36_close_penVETORf.mat' ...
'S37_close_penVETORf.mat' ...
'S38_close_penVETORf.mat' ...
'S40_close_penVETORf.mat' ...
'S44_close_penVETORf.mat' ...
'S45_close_penVETORf.mat' ...
'S46_close_penVETORf.mat' ...
'S48_close_penVETORf.mat' ...
'S51_close_penVETORf.mat' ...
'S55_close_penVETORf.mat' ...
'S57_close_penVETORf.mat'};

N_subjects = length(file_open_10); % numero de sujeitos

% open_10 X open_pen
file_out = '/home/evandro/matriz_Open10XOpenPen.csv';
for i=1:N_subjects
    load(fullfile(folder_open, file_open_10{i}));
    d1 = d;
```

```
    for j=1:N_subjects
        load(fullfile(folder_open, file_open_pen{j}));
        d2 = d;
        Euc_dist(I,j) = sqrt(sum((d1 - d2).^2));
    end
end
csvwrite(file_out,Euc_dist);

% open_10 X close_pen
file_out = '/home/evandro/matriz_Open10XClosePen.csv';
for i=1:N_subjects
    load(fullfile(folder_open, file_open_10{i}));
    d1 = d;
    for j=1:N_subjects
        load(fullfile(folder_close, file_close_pen{j}));
        d2 = d;
        Euc_dist(i,j) = sqrt(sum((d1 - d2).^2));
    end
end
csvwrite(file_out,Euc_dist);
```

6E+05	3E+06	2E+06	4E+06	1E+06	7E+05	1E+06	7E+05	7E+05	1E+06	9E+05	2E+06	2E+06	9E+05	6E+05	940570	1E+06	1E+06	1E+06	7E+05	6E+05	3E+06	1E+06	9E+06	6E+05	1E+06	2E+06	1E+06	1E+06	9E+0
3E+06	2E+06	3E+06	3E+06	3E+06	3E+06	3E+06	3E+06	3E+06	3E+06	3E+06	3E+06	2E+06	3E+06	3E+06	3E+06	4E+06	3E+06	4E+06	3E+06	3E+06	3E+06	2E+06	8E+06	3E+06	3E+06	2E+06	3E+06	3E+06	3E+0
1E+06	3E+06	1E+06	3E+06	2E+06	2E+06	2E+06	1E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	1E+06	8E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+0
3E+06	3E+06	3E+06	2E+06	4E+06	4E+06	4E+06	3E+06	4E+06	4E+06	4E+06	3E+06	3E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	2E+06	3E+06	7E+06	4E+06	3E+06	3E+06	4E+06	4E+06	4E+0
1E+06	4E+06	3E+06	5E+06	3E+05	7E+05	4E+05	1E+06	6E+05	4E+05	5E+05	2E+06	2E+06	5E+05	9E+05	624130	4E+05	4E+05	4E+05	6E+05	8E+05	4E+06	2E+06	1E+07	7E+05	2E+06	3E+06	4E+05	4E+05	8E+0
8E+05	3E+06	2E+06	4E+06	1E+06	9E+05	1E+06	9E+05	1E+06	1E+06	1E+06	2E+06	2E+06	1E+06	8E+05	1E+06	1E+06	1E+06	1E+06	8E+05	1E+06	3E+06	2E+06	9E+06	8E+05	1E+06	2E+06	1E+06	1E+06	1E+0
1E+06	4E+06	3E+06	5E+06	4E+05	8E+05	3E+05	1E+06	6E+05	3E+05	5E+05	2E+06	3E+06	5E+05	1E+06	687340	2E+05	4E+05	2E+05	8E+05	9E+05	4E+06	2E+06	1E+07	7E+05	2E+06	3E+06	3E+05	3E+05	8E+0
1E+06	3E+06	2E+06	4E+06	2E+06	1E+06	2E+06	8E+05	1E+06	2E+06	1E+06	2E+06	2E+06	1E+06	1E+06	1E+06	2E+06	1E+06	2E+06	1E+06	1E+06	3E+06	1E+06	9E+06	1E+06	1E+06	2E+06	2E+06	2E+06	1E+0
1E+06	4E+06	3E+06	5E+06	3E+05	7E+05	3E+05	1E+06	5E+05	3E+05	4E+05	2E+06	2E+06	4E+05	9E+05	627820	3E+05	3E+05	2E+05	7E+05	8E+05	4E+06	2E+06	1E+07	6E+05	2E+06	3E+06	2E+05	2E+05	7E+0
1E+06	4E+06	3E+06	5E+06	4E+05	8E+05	4E+05	1E+06	6E+05	2E+05	5E+05	2E+06	3E+06	5E+05	1E+06	702500	3E+05	4E+05	2E+05	8E+05	9E+05	4E+06	2E+06	1E+07	8E+05	2E+06	3E+06	2E+05	3E+05	8E+0
1E+06	4E+06	3E+06	5E+06	4E+05	8E+05	4E+05	1E+06	7E+05	3E+05	6E+05	3E+06	3E+06	5E+05	1E+06	724730	2E+05	4E+05	2E+05	8E+05	9E+05	4E+06	2E+06	1E+07	8E+05	2E+06	3E+06	2E+05	2E+05	9E+0
4E+06	5E+06	5E+06	5E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+06	5E+06	4E+06	9E+06	4E+06	4E+06	4E+06	4E+06	4E+06	4E+0
3E+06	3E+06	3E+06	4E+06	3E+06	3E+06	3E+06	3E+06	3E+06	3E+06	3E+06	2E+06	2E+06	3E+06	3E+06	3E+06	4E+06	3E+06	4E+06	3E+06	3E+06	2E+06	2E+06	8E+06	3E+06	2E+06	2E+06	3E+06	3E+06	3E+0
1E+06	4E+06	3E+06	5E+06	4E+05	7E+05	3E+05	1E+06	5E+05	3E+05	4E+05	2E+06	2E+06	4E+05	9E+05	649860	2E+05	3E+05	2E+05	7E+05	8E+05	4E+06	2E+06	1E+07	7E+05	2E+06	3E+06	2E+05	2E+05	8E+0
1E+06	4E+06	3E+06	5E+06	4E+05	6E+05	4E+05	1E+06	5E+05	4E+05	4E+05	2E+06	2E+06	4E+05	8E+05	631230	4E+05	3E+05	4E+05	6E+05	8E+05	4E+06	2E+06	1E+07	6E+05	2E+06	3E+06	3E+05	4E+05	7E+0
2E+06	3E+06	2E+06	3E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	3E+06	2E+06	2E+06	2E+06	2E+06	2E+06	1E+06	8E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+0
1E+06	4E+06	3E+06	5E+06	4E+05	9E+05	4E+05	2E+06	7E+05	4E+05	6E+05	3E+06	3E+06	6E+05	1E+06	757330	2E+05	4E+05	2E+05	9E+05	1E+06	4E+06	2E+06	1E+07	8E+05	2E+06	3E+06	3E+05	3E+05	9E+0
1E+06	3E+06	3E+06	4E+06	8E+05	7E+05	7E+05	1E+06	6E+05	8E+05	8E+05	2E+06	2E+06	7E+05	8E+05	810170	9E+05	7E+05	9E+05	8E+05	7E+05	3E+06	2E+06	1E+07	7E+05	2E+06	3E+06	8E+05	8E+05	8E+0
1E+06	4E+06	3E+06	5E+06	4E+05	9E+05	4E+05	2E+06	7E+05	4E+05	6E+05	3E+06	3E+06	6E+05	1E+06	760010	1E+05	4E+05	2E+05	9E+05	1E+06	4E+06	2E+06	1E+07	9E+05	2E+06	3E+06	2E+05	2E+05	9E+0
1E+06	4E+06	3E+06	5E+06	3E+05	8E+05	3E+05	1E+06	5E+05	3E+05	5E+05	2E+06	2E+06	4E+05	1E+06	661760	2E+05	3E+05	2E+05	7E+05	8E+05	4E+06	2E+06	1E+07	7E+05	2E+06	3E+06	2E+05	2E+05	8E+0
9E+05	3E+06	2E+06	4E+06	6E+05	5E+05	6E+05	1E+06	5E+05	6E+05	4E+05	2E+06	2E+06	4E+05	7E+05	658050	7E+05	6E+05	7E+05	4E+05	5E+05	3E+06	2E+06	9E+06	5E+05	1E+06	3E+06	6E+05	6E+05	7E+0
1E+06	3E+06	2E+06	3E+06	2E+06	2E+06	2E+06	1E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	2E+06	1E+06	8E+06	2E+06	1E+06	2E+06	2E+06	2E+06	2E+0
3E+06	3E+06	3E+06	3E+06	4E+06	3E+06	3E+06	3E+06	3E+06	3E+06	3E+06	2E+06	2E+06	3E+06	3E+06	3E+06	4E+06	3E+06	4E+06	3E+06	3E+06	2E+06	2E+06	8E+06	3E+06	2E+06	2E+06	4E+06	4E+06	3E+0
3E+06	3E+06	3E+06	3E+06	4E+06	3E+06	4E+06	3E+06	3E+06	4E+06	3E+06	3E+06	2E+06	4E+06	3E+06	4E+06	4E+06	4E+06	4E+06	3E+06	3E+06	2E+06	2E+06	7E+06	3E+06	3E+06	2E+06	4E+06	4E+06	3E+0
8E+05	3E+06	2E+06	4E+06	1E+06	9E+05	1E+06	7E+05	1E+06	1E+06	1E+06	2E+06	2E+06	1E+06	9E+05	1E+06	2E+06	1E+06	1E+06	9E+05	9E+05	3E+06	1E+06	9E+06	9E+05	1E+06	2E+06	1E+06	1E+06	1E+0
2E+06	3E+06	3E+06	4E+06	3E+06	2E+06	3E+06	2E+06	2E+06	3E+06	3E+06	2E+06	2E+06	3E+06	2E+06	3E+06	3E+06	3E+06	3E+06	2E+06	2E+06	2E+06	2E+06	9E+06	2E+06	1E+06	2E+06	3E+06	3E+06	3E+0
5E+06	4E+06	4E+06	4E+06	6E+06	5E+06	6E+06	5E+06	5E+06	6E+06	5E+06	4E+06	4E+06	5E+06	5E+06	5E+06	6E+06	6E+06	6E+06	5E+06	5E+06	3E+06	4E+06	7E+06	5E+06	4E+06	3E+06	6E+06	6E+06	5E+0
1E+06	4E+06	3E+06	5E+06	4E+05	7E+05	4E+05	1E+06	5E+05	3E+05	4E+05	2E+06	2E+06	4E+05	9E+05	619580	4E+05	3E+05	4E+05	6E+05	7E+05	4E+06	2E+06	1E+07	6E+05	2E+06	3E+06	3E+05	3E+05	7E+0
1E+06	4E+06	3E+06	5E+06	4E+05	8E+05	3E+05	1E+06	6E+05	3E+05	5E+05	2E+06	3E+06	4E+05	1E+06	707660	2E+05	4E+05	2E+05	8E+05	9E+05	4E+06	2E+06	1E+07	8E+05	2E+06	3E+06	2E+05	2E+05	9E+0
7E+05	3E+06	2E+06	4E+06	1E+06	8E+05	1E+06	8E+05	9E+05	1E+06	1E+06	2E+06	2E+06	1E+06	8E+05	1E+06	1E+06	1E+06	1E+06	9E+05	8E+05	3E+06	1E+06	9E+06	8E+05	1E+06	2E+06	1E+06	1E+06	8E+0