Analysis of Brain Waves in Violent Images
Are Differences in Gender?

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Abstract: We collected information using the Electroencephalograph (EEG) EmotivEpoc, and the software complement of the Eye Tracking system SMI RED250mobile. As a first step, it was stored in text files, the readings of each EEG sensor during the time the presentation of 5 violent images and 5 non-violent images were observed. The database was collected with 50 volunteers, consisting of 25 men and 25 women. The database was later loaded into R, for the execution of the algorithms of data mining, K-means, K-medoids, Hierarchical Clustering, Naive Bayes, Support Vector Machines, Adaboost and Decision trees. In the clustering methods, a random clustering was presented and with little information, with the Naive Bayes, SVM and Adaboost models, a classification with a high percentage of error was obtained using the Decision Trees method, we obtained one of the worst results, with the highest error rates in the classification performed with the test data of selected method. Based on the results obtained, no significant difference was found in the individual's gender, which affected his reaction when viewing images with violent and non-violent content.

1 INTRODUCTION

Humans analyze and react in different ways when see or observe different situations; however, it is desirable to identify patterns that allow classification.

Due to the easy access to Internet, people can access to a lot of information, but this privilege has brought with it a great danger, graphic violent content may be unfit or disturbing for many people. As a result, several works have been done related with the classification of videos and images into violent and non-violent content under different criteria, which has been a topic of interest and research in recent years.

In this project we analyzed the brain waves of people when they witnessed images that could be classified as violent or non-violent, in order to compare the results obtained, for determining if there are differences or not in the gender.

First we acquire brainwave data of people observing the violent and non-violent images using the EmotivEpoc, this data was stored in a database. Then, this data was schematized using the software R, and processed using some data mining algorithms using packages of the same software. The goal was to classify the samples in at least two groups, Male and Female samples. The EmotivEpoc is a wireless EEG of 14 channels, designed for research and advanced brain computer interface.

There are some related works about violence in images and videos; recognizing acts of violence on videos with crowds, without audio (Hassner, 2012). Classifying images in violent and non-violent using the BoW model integrated with the SPM scheme and soft voting strategy (Wang, 2012). There area also some works related with the consequences of watching violence on TV (Tisserom, 2006), and recording with an EEG how young men react while they do a laboratory test called Taylor Aggression Paradigm (Wiswede, 2011). A recent work (Manrique, 2014) used some data mining algorithms to classify the sound of firearms shots.

(Lotte, 2007) focus on the classification algorithms used to design EEG-based Brain-Computer Interface (BCI) and the used features, they aware that problems may be different if used outside the laboratories. The classification algorithms used to design BCI systems were divided into five categories: a) Linear classifiers (LDA, Linear Discriminant Analysis and SVM, Support Vector Machine), b) Neural Networks (MLP, MultiLayer Perceptron and other architectures), c) NonLinear Bayesian classifiers (Bayes quadratic and HMM, Hidden Markov Model), d) Nearest Neighbor classifiers

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(kNN and Mahalanobis distance) and e) combinations of classifiers. They conclude that SVM are particularly efficient for synchronous BCI and combinations of classifiers and dynamic classifiers also result very efficient in synchronous experiments.

The present work pretends to be an antecedent of future studies on repercussions to the mind of the human being when observing violent content, depending if the person observing it is of the feminine or masculine gender. The goal, carrying out a study on the cerebral activity that generates the viewing of images classified as violent or non-violent, is trying to detect whether is a difference in gender or not.

For the statistic analysis and data mining prcess, was used the R software. R is a GNU project that has a wide variety of statistical and graphical techniques and is extensible. It is a complete computer language and allow additional funcionality so it can be extended via packages (R, 2017).

The general diagram is presented in Figure 1.

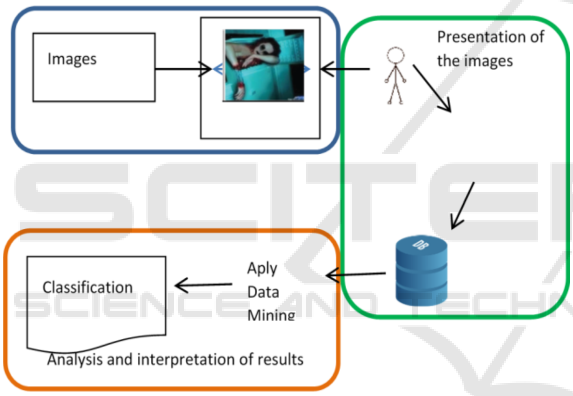

Figure 1: Components diagram of the project.

This paper is organized as follows, in section 2 we present the process for collecting the information, which includes the construction of the database, presentation of images and the collection of EEG data. In section 3, we present the analysis and the interpretation of results obtained from each algorithm. Finally, in section 4, we expose our conclusion and comment about future related works.

2 GATHERING INFORMATION

2.1 Building the Image Database

There is no database available with classified images in violence and no violence, so we had to make one, by searching and collecting images through the online search engine “Google”, using query words such as “violence”, “horror”, “explosion”, “blood”, “shots”, “war”, and similar, to those used in the construction of the VID database (Wang, 2012). After creating the database, 10 images were selected, 5 classified as violent and 5 non-violent, by personal criteria of a group of undergraduate and graduate students. For the presentation that would be shown to the volunteers of the project, these images must had a minimum resolution of approximately 1000x800 and 1200x1000 pixels. These images must maintain a certain parallelism of the contents, as for example: people, scenes, objects, etc.

2.2 Image Presentation

Violent and non-violent images were presented with the help of the Eye Tracking system, 50 volunteers from the university community, 25 from male gender and 25 from female gender. First we had to place the EEGdevice, which requires that the electrodes were sufficiently hydrated with saline solution for the correct measurement, so that some potential volunteers, could not perform the test due to hair products that blocked or didn’t allowed the electrodes to contact the skin.

2.3 Collecting the EEG Data

After having placed the data channels and obtained a good signal of the EmotivEpoc device, we proceeded to the present the violent and non-violent images in a monitor.

Each image was exposed for three-second to each volunteer, that duration was selected by suggestion of M.D. Roberto García, whom from personal experience of previous works, pointed out that it didn’t require more time for the image to cause a reaction in the observer.

After collecting the EEG data of the 50 volunteers, the EEG database was extracted with the SMI Experiment Suite software in the Laboratory, which also allowed us to observe the path of the volunteer’s vision during the exposure to the picture.

The database information was processed to a text file, separated by tabulations, which contains: name of the volunteer, name of the image that was observed at a moment, values registered from the 14 electrodes, information of the gyroscope and emotion values that were automatically calculated by the EEG device, with an average performance of 60 values per second registered by the EmotivEpoc diadem.

3 ANALYSIS AND INTERPRETATION OF RESULTS

Due to the large amount of data obtained through the EmotivEpoc equipment, since several values per second were extracted in each of the electrodes, we proceeded to form tables, as objects of R, where for each volunteer their maximum, mean, median and variance values of each EEG channel were showed during the exposure of each of the violent and non-violent images.

It should be mentioned that in the creation of tables, a column was added, indicating if the sample corresponded to a person of masculine or feminine gender, this, for its later use in algorithms of data mining. In the same way, three columns were excluded, because two of them were signal of the gyroscope integrated to the EEG device, and another one, sampled an extra value to the 14 necessary electrodes, that very concurrently took a null value.

At this stage, the R table objects are analyzed through the application of clustering, classification and automatic learning methods, for determining if these algorithms were able to recognize or predict the gender of the volunteer.

All the data mining techniques used in this project took as parameters the columns corresponding to the maximum, mean, median and variance values that the EEG channels of the EmotivEpoc diadem produced, and the rows represent the samples of the volunteers during the time of exposure to the images.

3.1 Data Mining Algorithms

In this section we present the main results obtained using K-means, K-medoids, hierarchical clustering, support vector machines, decision trees, Naive Bayes, and Adaboost.

In the results presented in the form of tables, contractions will be used for naming generated datasets, e.g. v1, v2 and v3, refer to violent images one, two and three, while nv1, nv2 and nv3, refers to non-violent images one, two and three, likewise, for sets with maximum (max), mean (mean), median (median) and variance (var), resulting in naming the datasets generated in this way, for example: v1max, v3mean, nv2median, nv5var.

When executing the K-means method, with two and three clusters, a very large cluster were formed, and one or two with few objects in it, as can be seen in Table 1.

Table 1: K-means with maximum values using k=2 & k=3.

Data	Clusters size				
	k=2		k=3		
	Cluster 1	Cluster 2	Cluster 1	Cluster 2	Cluster 3
v1max	1	49	1	5	44
v2max	5	45	44	2	4
v3max	5	45	3	2	45
v4max	8	42	9	39	2
v5max	5	45	39	8	3
nv1max	1	49	40	1	9
nv2max	8	42	8	41	1
nv3max	1	49	45	4	1
nv4max	46	4	40	6	4
nv5max	7	43	7	1	42

We increased the “k” number of clusters to 10, due to the results observed with 2 and 3 clusters, trying to divide the main cluster who appeared using k=2 & k=3, hoping that the new clusters could contain sub-groups from one gender, or other classifications, unfortunately the clusters created did not include sub-groups from just one gender, and at that moment, we did not asked to the volunteers for their personal information, such as age, occupation, or other relevant data.

Obtained results with k from 2 to 10 were very similar, small clusters and always one of a larger size, as can be seen in Table 2.

Table 2: K-means with maximum values using k=10.

Data	Cluster and size									
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
v1max	1	1	2	7	1	3	4	1	6	24
v2max	5	6	2	1	4	3	1	3	24	1
v3max	1	19	1	2	7	1	2	9	2	6
v4max	18	1	11	6	2	1	1	1	5	4
v5max	3	4	5	2	1	11	15	4	3	2
nv1max	2	8	2	3	4	1	1	25	1	3
nv2max	16	3	1	1	1	4	9	8	3	4
nv3max	1	1	1	1	13	26	1	1	1	4
nv4max	1	1	3	4	1	1	19	10	5	5
nv5max	1	2	28	1	2	1	1	9	4	1

When applying the K-medoids method, using any of the two functions of R, pam () and pamk (), the results obtained did not generate any distinction between the genders. As discussed in Tables 3 and 4, on the use of these methods, there was the same problem as with the use of K-means, a cluster was formed that contained most of the objects, and another one with little amount of data.

Table 3: pam() with mean values using k=2.

Data	Clusters Size	
	C1	C2
v1mean	43	7
v2mean	48	2
v3mean	45	5
v4mean	43	7
v5mean	49	1
nv1mean	49	1
nv2mean	48	2
nv3mean	49	1
nv4mean	47	3
nv5mean	49	1

Table 4: pam() with mean values.

Data	Clusters Size			
	C1	C2	C3	C4
v1mean	41	1	7	1
v2mean	48	2		
v3mean	45	5		
v4mean	43	7		
v5mean	49	1		
nv1mean	49	1		
nv2mean	48	2		
nv3mean	49	1		
nv4mean	47	3		
nv5mean	49	1		

In the call to the hierarchical clustering method it was noticed that was generated a similar result to the previously described clustering methods, when partitioning in 10 clusters, the *dendrogram* printed by the method showed a cluster with most objects and very small ones, It can also be seen in Figure 2 that objects or samples belonging to both genders (M and F) are housed in the formed clusters.

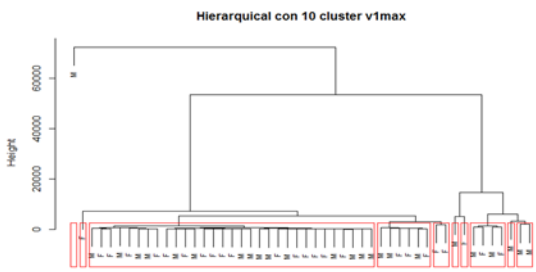

Figure 2: Hierarquical Clustering using k=10.

Training a SVM for classification and regression involves solving a quadratic optimization problem. Using a standard quadratic problem solver for training an SVM would involve solving an exponential problem. To handle this issue, methods like SMO (Platt 1998), chunking (Osuna et al., 1997) and simple SVM (Vishwanathan et al., 2003) exist that iteratively compute the solution of the SVM and scale O(N2.5). In package e1071 (Karatzoglou et al., 2006), used in this project, the training patterns, called support vectors, carry all relevant information about classification problem.

The results obtained using the SVM algorithm on the different tables didn't show a good solution when classifying test data. As can be seen in Tables 5 and 6, where the percentage of correctness and error obtained on the classification of the selected samples.

Table 5: SVM with maximum values using lineal kernel.

Data	%	
	Error	Success
v1max	42.1053	57.89474
v2max	38.4615	61.53846
v3max	71.4286	28.57143
v4max	50	50
v5max	42.8571	57.14286
nv1max	50	50
nv2max	38.4615	61.53846
nv3max	41.1765	58.82353
nv4max	57.8947	42.10526
nv5max	37.5	62.5

Table 6: SVM with variance values using lineal kernel.

Data	%	
	Error	Success
v1var	28.5714	71.42857
v2var	66.6667	33.33333
v3var	41.1765	58.82353
v4var	36.3636	63.63636
v5var	50	50
nv1var	50	50
nv2var	44.4444	55.55556
nv3var	46.1538	53.84615
nv4var	50	50
nv5var	38.4615	61.53846

The results obtained using the Naive Bayes algorithm yielded very different percentages of error and correctness in classifying the test data, as can be seen in Tables 7 and 8, showing a very erratic classification in the majority of the tests performed.

Table 7: Naïve Bayes with mean values.

Data	%	
	Error	Success
v1mean	27.2727	72.72727
v2mean	41.6667	58.33333
v3mean	41.6667	58.33333
v4mean	42.8571	57.14286
v5mean	60	40
nv1mean	41.1765	58.82353
nv2mean	20	80
nv3mean	40	60
nv4mean	60	40
nv5mean	33.3333	66.66667

Table 8: Naïve Bayes with maximum values.

Data	%	
	Error	Success
v1max	42.8571	57.14286
v2max	50	50
v3max	55.5556	44.44444
v4max	28.5714	71.42857
v5max	50	50
nv1max	63.6364	36.36364
nv2max	55.5556	44.44444
nv3max	36.3636	63.63636
nv4max	44.4444	55.55556
nv5max	45.4545	54.54545

The results obtained using the classification algorithm with a decision tree, showed a very low percentage of correctness in the gender classification of the test objects as can be seen in Tables 9 and 10.

Table 9: Decision tree with maximum values.

Data	%	
	Error	Success
v1max	53.8462	46.15385
v2max	61.1111	38.88889
v3max	52.9412	47.05882
v4max	53.3333	46.66667
v5max	58.8235	41.17647
nv1max	56.25	43.75
nv2max	50	50
nv3max	73.3333	26.66667
nv4max	57.1429	42.85714
nv5max	53.8462	46.15385

Table 10: Decision tree with mean values.

Data	%	
	Error	Success
v1mean	68.75	31.25
v2mean	52.6316	47.36842
v3mean	57.8947	42.10526
v4mean	53.8462	46.15385
v5mean	53.8462	46.15385
nv1mean	52.9412	47.05882
nv2mean	70	30
nv3mean	60	40
nv4mean	62.5	37.5
nv5mean	61.5385	38.46154

The results obtained using Adaboost on the data set did not obtain a good solution when classifying samples by gender, obtaining very high percentages of error, as shown in Tables 11 and 12.

Table 11: Adaboost with maximum values.

Data	%	
	Error	Success
v1max	42.1053	57.89474
v2max	38.8889	61.11111
v3max	42.8571	57.14286
v4max	60	40
v5max	27.7778	72.22222
nv1max	52.9412	47.05882
nv2max	47.0588	52.94118
nv3max	30	70
nv4max	42.1053	57.89474
nv5max	50	50

Table 12: Adaboost with median values.

Data	%	
	Error	Success
v1median	58.3333	41.66667
v2median	18.75	81.25
v3median	43.75	56.25
v4median	50	50
v5median	35.2941	64.70588
nv1median	41.6667	58.33333
nv2median	37.5	62.5
nv3median	66.6667	33.33333
nv4median	47.0588	52.94118
nv5median	30	70

4 CONCLUSIONS

A database was obtained through the EmotivEpoc EEG device and specialized software for the collecting raw data which was analyzed with several algorithms and data mining methods, in order to determine if there was a difference in gender when observing violent images. The database was built, showing for thirty seconds, five violent images and five non-violent images (three seconds per image) to a group of 50 volunteers, of whom half were women and the other half men.

The K-means method applied to all generated tables, didn't show good results, performing a separation of 2, 3 and 10 clusters, in all cases, was created a cluster which groups the majority of the objects of both genders, and others clusters were very small, grouping up to a single object, from which it's deduced that it's not a good classification.

The Hierarquical method used didn't obtain different results to the K-means, the cut was carried out to 10 clusters and it's observed that the clusters contain one or very few objects of both genders, and there are one or two clusters of bigger size, that contain the majority of samples for both genders. So we didn't get a good gender classification with this Hierarquical method. Using the K-medoids method to the calculated values tables, good results weren't also generated, using the pam() function of R, results obtained were similar to K-means with two clusters, since a cluster contained almost all of the samples, and in these clusters, no gender classification was found. With the pamk() function of R, we obtained similar results to those of the pam() function, however in some cases, it generated one or two more clusters, although this didn't result in a better classification, since a large cluster was maintained, there wasn't any classification that could be identified due to gender.

The Support Vector Machine (SVM) with linear kernel, didn't produce better results than the clustering methods mentioned above, reaching, in the worst cases, a success rate that was around 30-45%, considering that it didn't obtain a good classification of gender due to it classified all the samples of test like a single gender.

The Naive Bayes classification algorithm presented results with very little success percentage on the test data, the less successful tests were around 40% and the best classification was between 70% and 80%, although there were many tests with results between these cases, it was not possible to obtain good conclusions for using this algorithm in gender classification of objects.

The decision trees methods gave us very high rates of error in the gender classification, reaching over 70% error and not less than 50% on the test data. This indicates that this algorithm was not useful for the classification of the samples of the database.

Finally, the Adaboost algorithm registered an error rate between 40% and 70%, just as with the percentage of success in the tests, the model created fails to distinguish with certainty the samples in order to classify them by gender.

Summarizing, the results obtained when using clustering methods didn't achieve a minimum classification, as the number of clusters increased, the cluster in which the majority of the samples were concentrated didn't decrease considerably its size, and only generated other clusters with even a single object. Thus, the results of these clustering methods were not expected, since they failed to recognize or classify the samples of different gender and the generated clusters were very different in size and samples of the same gender contained.

About using Support Vector Machines, Naïve Bayes and Adaboost, the obtained results were not as expected, since the formed models failed to perform a classification of the test data with a considerable percentage of success, reaching a success rate that was around 40% to 60%.

Considering this, can be told that none of the algorithms and methods presented and used here were able to classify a reaction of viewing violent images per gender.

In the execution of this project the specific objectives were fulfilled, based on the results obtained from the application of data mining algorithms, it was not possible to determine if there is a difference in gender when observing violent and non-violent images. Probably the study should be carried out with a larger number of people, belonging to a more specific range of age, and a community better delimited to avoid in a certain way that isolated cases affect the methods of data mining, and so perhaps to obtain other conclusions.

Other factors may affect outcomes, such as age, environment, vision problems, past events that may psychologically affect the human being, use of drugs, medicines, or substances can affect the nervous system

In the development of the project we presented certain problems that were solved with a better use of the R environment for data management, although the notions acquired from the R language were sufficient for the application of data mining is expected to extend this knowledge of Data mining in the future.

In order to carry out related future work, the opinion of experts on violence should be considered in order to determine the initial classification of the images to be used, it should also be taken into account that gender is not the only thing that can be inferred in the reaction of the human brain before the visualization of violent images or not.

Also, the creation of a more extensive database with a greater number of participants, in order to be able to contemplate cases that reacted abnormally to the presence of violence could help in the training stage for several algorithms such as SVM or Adaboost. It could also be an option, to use videos with violent or non-violent content instead of images for future works.

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