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The Entropy of Laughter: Discriminative Power of Laughter's Entropy in the Diagnosis of Depression

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Abstract: Laughter is increasingly present in biomedical literature, both in analytical neurological aspects and in applied therapeutic fields. The present paper, bridging between the analytical and the applied, explores the potential of a relevant variable of laughter's acoustic signature—entropy—in the detection of a widespread mental disorder, depression, as well as in gauging the severity of its diagnostic. In laughter, the Shannon–Wiener entropy of the distribution of sound frequencies, which is one of the key features distinguishing its acoustic signal from the utterances of spoken language, has not been a specific focus of research yet, although the studies of human language and of animal communication have pointed out that entropy is a very important factor regarding the vocal/acoustic expression of emotions. As the experimental survey of laughter in depression herein undertaken shows, it was possible to discriminate between patients and controls with an 82.1% accuracy just by using laughter's entropy and by applying the decision tree procedure. These experimental results, discussed in the light of the current research on laughter, point to the relevance of entropy in the spontaneous *bona fide* extroversion of mental states toward other individuals, as the signal of laughter seems to imply. This is in line with recent theoretical approaches that rely on the optimization of a neuro-informational free energy (and associated entropy) as the main "stuff" of brain processing.

Keywords: entropy of laughter; neuropsychiatry; depression; laughter; sound structures; plosives

1. Introduction

It is a fact that biomedical research on laughter has notoriously increased during the last decades, not only in volume of publications but also in the number of specialized disciplines involved. In PubMed, under the heading of laughter, there were 32 publications in the 1940s and 1950s; 119 in the 1960s and 1970s; 585 in the 1980s and 1990s; and 1044 publications in the 15 years since 2000. Nowadays, laughter has become an interesting research topic under an ample variety of perspectives: biomedical, biophysical, neuro-computational, cognitive, psychological, social, evolutionary, philosophical, engineering... As always happens, with the augmented volume of research and the very different points of view, the list of unanswered questions to investigate grows and grows. One of these questions, the role of entropy, is the focus of the present paper.

Laughter, as a conspicuous interpersonal communicative signal (Kierkegaard noted that a solitary laugh was "a little more than queer"), is ordinarily related to the use of language [1]. From the evolutionary point of view, however, laughter has preceded language. Anthropoid ritualized "panting" during play may be considered as the closest antecedent of human laughter [2]. The increasing group size of humans and the parallel increase in brain size—both of them crucial for the emergence of linguistic skills [3]—projected laughter to a new, more complex social scenario. Rather than being expressed only as an individual's signal of commitment to play, it became an important group display containing a variety of underlying emotional expressions and relational categories. Its sound structures also became more complex and more capable of expressing the situational nuances, based on an improved control of breathing as well [1,4–6]. Thereafter, the occurrence of laugher became regularly tied to all kinds of inter-individual relationships, quite often via language, punctuating behavioral situations or linguistic utterances as a sort of emotional valuation of the congruence with the shared background of the other individual or of the group audience.

1.1. The Social Meaning of Laughter

Convivially, rather than being the result of clever jokes or sophisticate humorous constructs, most laughter is produced around small talk in a variety of social environments: at home, with friends, at the workplace, during courtship, along children's play, in group coalitions, at the "third place" [1,7–9], *etc*. Following the strong "grooming" connotations of human language that have been advocated by the "social brain hypothesis" [10–12], laughter conspicuously appears as a physiological intensification of such linguistic grooming. It is a signal of being cooperative, and an indirect way to rebuild and to strengthen the memory traces involved in the ongoing interaction. Laughing is about making more robust bonds between the participants in the interaction, crystallizing a shared sense of belonging. Whenever there are human bonds in the making, laughter is instinctively put into action [13,14].

Why does the acoustic signal of laughter have such powerful effects? Apparently, the acoustic signature of laughter is well known; nevertheless, it still contains intriguing elements. It may be summarized [15] as composed of behavioral *episodes* that contain several *bouts* (with exhalation parts separated by brief inhalations) that in their turn are composed of several laughter *plosives* (calls, syllables, pulses). Amongst the most important sound characteristics that appear there: the fundamental frequency F_0 of the emitted sounds, the changes and excursions of this fundamental frequency between plosives, the irregular separation between plosives, the "vowels" of the voiced laughter (*versus* the unvoiced laughter), as well as the energy, amplitude, and entropy related to the distribution of intervening frequencies. It is at least intriguing that the entropy of laughter is higher than the entropy of spoken language [16]. As will be discussed later on, this difference might indicate two things: that the neural control involved in laughter emission is "more primitive" (clearly, different neural circuits are involved in the control of vowel cords and the whole respiratory–phonatory apparatus); and additionally that an increased entropic distinctiveness of the received laughter may increase its attractiveness and improve the emotional sharing [17]. The theme will also be discussed regarding the interrelationship of neural entropy with the general "stuff" of brain processing [18,19]. About the specific phonation involved, the facial counterparts, the diaphragmatic and bodily movements, and the systemic repercussions (cardiovascular, immune, central and autonomous nervous system, *etc.*), they will not be dealt with here [1,4,20], although they are essential to fulfill the "hidden" evolutionary missions of laughter and to explain most of the present therapeutic applications [13,21].

1.2. Biomedical Applications

Given the inner repercussions of producing and exchanging laughter, it is no wonder that biomedical applications have been multiplied during recent years, as already mentioned in the PubMed literature. Laughter has been widely explored as a therapeutic method to prevent and to treat major medical diseases—the positive effect of laughter and humor in pain relief, autoimmune pathologies, surgical recuperations, psychotherapy interventions, patient empowerment, general resilience, mental wellbeing, *etc.*, is well authenticated [7,21–24]. In mental pathologies, however, very few works have been addressed that explore the *discriminative potential* that laughter might contain. Quite probably, laughter is affected differently within the major neuropsychiatric pathologies, such as depression, schizophrenia, and psychoticism, as well as within dementia and neurodegenerative diseases [22,25–28]. All of these pathologies would have in common the diminished social ability of the individual to participate in group dynamics and to progress along bonding processes, as well as the relative blocking of the hedonistic mechanisms. In all of them, the emission of laughter would be either severely compromised or notoriously disorganized regarding the spontaneous response to humorous stimuli. However, as said, the relative specificity has not been found yet. Therefore, to the extent to which laughter reflects with some accuracy the specific mental condition of individuals [29], a better understanding of the whole sound structures of laughter could have relevant implications in mental-health research, beyond the present therapeutic applications—as, for instance, in diagnostics and prognosis, at detecting the differences between healthy subjects and patients, and at following the recovery progresses of patients. At least previous work by these authors [30] has demonstrated that simple proof based on laughter analysis can be useful in establishing the diagnostics of depression patients and gauging the severity of the disorder.

1.3. The Present Study

Our analytical focus in the present study will be specifically on entropy, complementing the previous study already mentioned [30]. In that work, we found that amongst the 10 acoustic variables considered for each plosive, three of them (energy, entropy, and F_0) had the highest discriminating power. Furthermore, given the relevance of entropy in the sound structures of animal communication, processing anew all of the data obtained and to check about the exclusive discriminating power of entropy regarding the physiological–emotional information contained within laughter's sound structures makes sense. Is entropy one of the fundamental components of the "emotional code" implicit in the communicative content of laughter? To the extent to which the answer is positive, it could contribute to refine and to improve the proposed use of laughter as a new tool, of easy and fast usage, for diagnosis and evaluation of neuropsychiatric diseases.

In that previous study, we were counting with registered laughs of depressed patients (n = 30) and healthy controls (n = 20), in total 934 laughs (517 from patients and 417 from controls). All patients were tested by the Hamilton Depression Rating Scale (HDRS). The records were processed using Matlab, evaluating the 10 following variables per plosive: time duration, fundamental frequency mean, standard deviation of the fundamental frequency, first three formants, average power or energy per sample, Shannon's entropy, jitter, shimmer, percentage of voiced/unvoiced signal, and harmonic to noise ratio. By applying general and discriminant analyses conducted in STATGRAPHICS Plus version 5.1 to those variables, we obtained discriminant functions, canonical correlations, Wilk's Lambda, and Fisher's linear discriminant function coefficients, showing that depressed patients and healthy controls differed significantly on the type of laughter, with 88% efficacy. In addition, according to the Hamilton scale, 85.47% of the samples were correctly classified in males, and 66.17% in women. After these results implying the 10 mentioned variables, what performances could be attained by means of the exclusive use of *entropy*?

In order to advance the present study, we have processed anew the 934 laughs already registered trying to analyze Shannon–Wiener entropy's specific contribution in discriminating power. To do that, we have constructed a *decision tree* and made a *cluster analysis* which shows the discriminating role of entropy. It is described below.

2. Material and Methods

2.1. Subjects

The 934 laughs registered belonged to 50 individuals, 30 patients and 20 healthy people, comprising men and women aged in between 20 and 65; their laughs were obtained in response to humorous videos (which were always watched accompanied by some acquaintance), and were registered individually by means of a directional digital voice recorder. More patients than controls were recruited in order to make possible a classification of depression rating and to correlate it with laughter registers. All of the individuals were Spanish and none of them was suffering any mental illness that prevented the realization of the task, so they could understand the humour sketches presented and complete the questionnaires. We followed the inclusion criteria described in [30] and the protocol was approved by the Regional Ethics Committee of Aragon.

2.2. Psychological Test

To measure the severity of clinical depression symptoms, all patients were tested by the Hamilton Depression Rating Scale (HDRS). The HDRS test is widely used to measure severity of depression and mood disorders both in clinical practice and research settings. In this study, we used the original 21-items version in its Spanish validated translation [31].

2.3. Compilation of Laughter

The compilation of humorous videos was made mainly by an Internet search. These videos provided funny circumstances to evoke laughter in most types of people (consisting of cartoon sketches, falls, jokes, famous movie characters, well-known humorists, *etc.*). A specific protocol was followed, including the different kinds of visual and acoustic stimuli used to generate laughter during sessions of 20 min. A digital voice recorder, Olympus VN-712PC (Olympus Imaging Corp., Tokyo, Japan), was used to capture the sound records.

Spontaneous laughter from each participant was registered in a wav archive encoded in 16-Bit PCM format, and was sampled in the 50–10,000 Hz interval. Every laugh episode was separated by both hearing the recordings and visualizing the waveforms provided by the sound analysis program Adobe Audition. Through this software, we could distinguish each laughter episode, so that the different laughter utterances were analysed, selected and stored separately. The evaluation of whether an audio segment was suitable or not, both for patients and controls, was mainly conditioned by its clarity (overlapped speech–laugh and laugh–laugh segments, as well as all kinds of exclamations and noises were dismissed). The resulting laugh archives were recorded from only one individual, had well defined boundaries, and did not include interfering sounds like coughs, throat clearing or humming—otherwise they were discarded. This evaluation job is too complicated to achieve with programmed laughter detectors, such as machine learning methods and support vector machines. The present manual process is slow but reliable enough.

According to the conventions already mentioned [15], each laughter *bout* contains a series of discrete elements, called *plosives*, which may be characterized as energy peaks separated by silences that are repeated every 200–220 ms approximately. This wide range of acoustic shapes requires segmentation in the time domain. At the temporal domain, bouts appear as alternating maxima and minima within the envelope of the waveform amplitude—and all the 10 variables already described may apply. However, in this study, as already mentioned, we will only work with the *entropy* of each plosive, following a statistical approach more appropriate to this circumstance: a *decision tree*.

2.4. Laughter Processing

In total, we compiled 934 well-formed laughs following the selection criteria just described (517 from patients and 417 from controls)—on average, 17 laughs for patients and 21 for controls. The plosive automatic detector was implemented in Matlab version R2014a. As an outcome of this characterization, a data matrix was obtained comprising all plosives sorted by individual laugh archives, each one in a row, with entropy values as the only column.

2.5. Statistical Analyses

A decision tree was built using SPSS version 22 (2014). Predictors were selected according to their statistical significance, thus enabling the detection of interactions with the values of those selected variables. For predictor variables, this technique [32] is capable of determining the optimal cut-off that maximizes the association with the entropy measure for each plosive: the entropy of the first (EP1), second (EP2), third (EP3), fourth (EP4), and fifth (EP5) plosives. Statistical significance was set for a probability $p < 0.01$.

Cluster analysis was conducted in SPAD.N version 8 (2014) using a mixed strategy that combined divisive and agglomerative techniques. The Euclidean squared distance and the minimal variance of Ward were used as the aggregation criterion. The number of clusters was determined by the aggregation criterion that describes a hierarchical tree followed by a reallocation of each case to the most nearest cluster by the *k*-average method. In this approach the number of clusters used is set up by the observer; and in our study six was taken as the optimal number of clusters. Finally, the characterization and description of clusters was conducted based on Lebart's statistical method [33], selecting those variables that are relevant to a cluster.

3. Results

3.1. Decision Tree

The decision tree distinguished depressed patients and healthy controls (Figure 1). The first input variable selected (node 0) is the entropy value measured in the first plosive (EP1) correctly classifying this variable to 71.2% of patients (EP1 > 0.00322) and 72.7% of control subjects (EP1 ⩽ 0.00322). According to the left nodes (1, 3) and branches of the tree, the probability of being a healthy person increases to 93.8% when the entropy of the first plosive is equal to or less than 0.00085. However, as seen on the right side of the tree, the probability of depression increases to 86.9% and 89.3% (nodes 5, 9) when the entropy measure in the fifth and second plosives is less than or equal to 0.00011 and 0.02342, respectively.

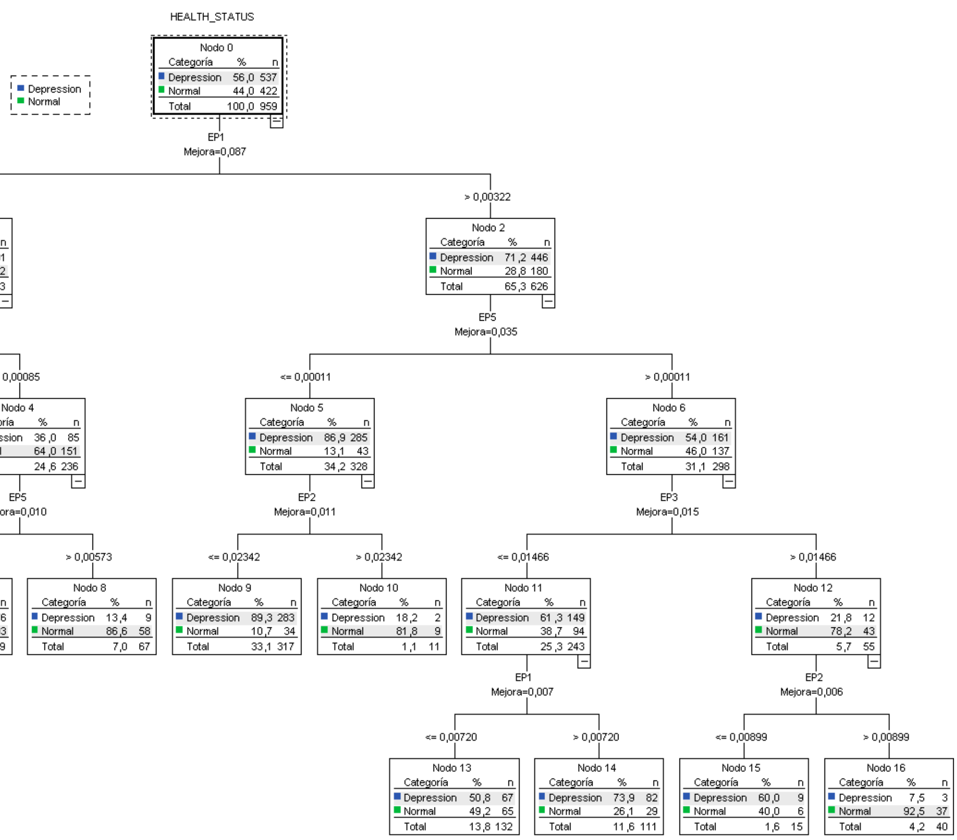

Figure 1. Decision tree showing depressed patients and healthy controls according entropy values measured at each plosive. This decision tree was conducted using IBM SPSS Decision Trees 22 (2014).

The decision tree (Figure 1) reveals the high discriminant role of the entropies of the first (EP1) and fifth (EP5) plosives. In order to obtain a classification of laughter according to the value of the entropies, the resulting decision tree allows us to establish the following taxonomy. Considering the aforementioned entropies EP1 and EP5 together with EP2 and EP3, we can get rules that classify nine types of laughter. Each class contains healthy and different percentages of depressed individuals: 6.2%, 7.5%, 13.4%, 18.2%, 45.0%, 50.8%, 60.0%, 73.9% and 89.3%. Based on the "0.5 rule", we obtained a successful classification of depressed patients and healthy controls (Table 1).

Table 1. Classification table of depressed patients and healthy controls based on the "0.5 rule".

Observed	Predicted		
	Patients	**Controls**	**Percent Correct**
Patients	441	96	82.1%
Controls	134	288	68.2%
Overall Percentage	60.0%	40.0%	76.0%

The decision tree (Figure 1) reveals the high discriminant role of the entropies of the first (EP1) and fifth (EP5) plosives. However, in order to obtain a classification of laughter according to the whole entropy values, the resulting decision tree allows us to establish the following taxonomy. Considering the aforementioned entropies EP1 and EP5 together with EP2 and EP3, we can get rules that classify nine types of laughter. Each class contains healthy and different percentages of depressed individuals: 6.2%, 7.5%, 13.4%, 18.2%, 45.0%, 50.8%, 60.0%, 73.9% and 89.3%. Based on the "0.5 rule"—a patient is classified to the most probable class with the highest percentage of diagnosis—we obtained a successful classification of depressed patients and healthy controls (Table 1). In general, the process resembles an expert system with certainty factors [34].

3.2. Cluster Analysis

The cluster analysis identified six types of laughter (Figure 2). According to the studied variables, the cluster obtained were: (1) healthy men (33% of cases); (2) depressed women (20% of cases); (3) depressed patients (26% of cases); (4) healthy controls (13% of cases); (5) depressed patients (6% of cases); and (6) healthy controls (3% of cases).

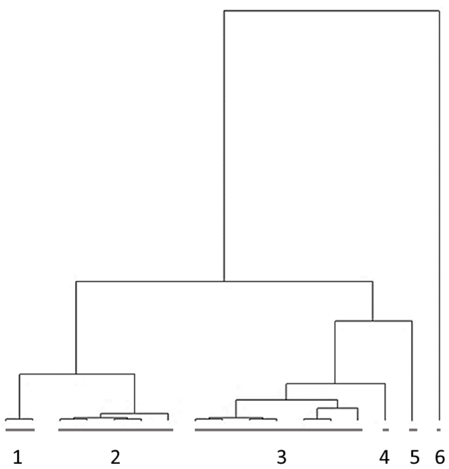

Figure 2. Cluster tree obtained after performing the clustering analysis using a mixed strategy. A total of 960 laughs were classified into six differentiated clusters.

Table 2 shows the partition description of each cluster showing with "−" the low values of entropy on a plosive, with "+" the high values of entropy, and "++" when very high values of entropy were measured in a plosive. If we only consider the first and fifth plosives, and classify clusters according to their individuals (clusters 1, 4 and 6 contain healthy control and clusters 2, 3 and 5 contain depressed patients), we conclude the following rule: "an individual is healthy when the value of entropy in the fifth plosive is relevant and is in synch with the value of the first plosive, or when both entropy values are high or both values are low". By contrast, an individual is depressed when the fifth plosive entropy is not relevant or has a low value.

Table 2. Partition description of each cluster, with "−" the low values of entropy on a plosive, with "+" the high values of entropy, and "++" when very high values of entropy were measured in a plosive.

	EP1	EP2	EP3	EP4	EP5
Cluster 1	−	−	−	−	−
Cluster 2	++	−	−	−	−
Cluster 3		+	+	−	−
Cluster 4			+	+	+
Cluster 5	++	+	+		
Cluster 6	+	+	++	++	++

Table 3 shows the summary statistics for each of the entropies studied. It is interesting to note that none of the entropies fits a normal distribution. It is also interesting to observe how the mean and median of entropy in the fifth plosive is very low or zero. This result would be consistent with what was observed in Table 2: that an individual suffering from depression shows a fifth plosive entropy that is no significant or with a very low value. Furthermore, the variability of entropy seems to be lower in depressed than in healthy subjects. In general, the results suggest that in depressed individuals a decrease in entropy occurs from the first to the fifth plosive. Although entropies have not normal distribution, normality is not required in the statistical tests performed since they are non-parametric statistical techniques [32].

Table 3. Statistical analysis of entropy values.

Entropy	Health Statuts	N	Mean	Standard Deviation	Median	Minimum	Maximum	*p*-Value *
EP1	Depression	537	0.0076	0.0054	0.0066	0.0005	0.0409	0.0000
	Normal	422	0.0045	0.0059	0.0026	0.0002	0.0472	0.0000
	Total	959	0.0062	0.0059	0.0050	0.0002	0.0472	–
EP2	Depression	537	0.0078	0.0055	0.0070	0.0000	0.0483	0.0000
	Normal	422	0.0098	0.0118	0.0062	0.0000	0.0818	0.0000
	Total	959	0.0087	0.0089	0.0067	0.0000	0.0818	–
EP3	Depression	537	0.0058	0.0058	0.0052	0.0000	0.0560	0.0000
	Normal	422	0.0097	0.0128	0.0064	0.0000	0.0954	0.0000
	Total	959	0.0075	0.0097	0.0056	0.0000	0.0954	–
EP4	Depression	537	0.0040	0.0048	0.0025	0.0000	0.0317	0.0000
	Normal	422	0.0077	0.0115	0.0050	0.0000	0.1068	0.0000
	Total	959	0.0056	0.0086	0.0036	0.0000	0.1068	–
EP5	Depression	537	0.0026	0.0040	0.0000	0.0000	0.0231	0.0000
	Normal	422	0.0064	0.0107	0.0030	0.0000	0.0916	0.0000
	Total	959	0.0042	0.0079	0.0012	0.0000	0.0916	–

* Shapiro–Wilks normality test.

When we measure only the entropies and compare them to other statistical techniques, the decision tree method leads to better results in the classification and diagnosis of subjects. Based on decision trees, we obtained a successful classification of depressed patients and healthy controls of 82.1% and 68.2% respectively, whereas using a binary logistic regression these percentages decreased to 79.1% and 64.0%, respectively. Similarly, using discriminant analysis, the success in the classification of depressed patients decreased to 65.7%, increasing to 76.5% in healthy controls. Considering all percentages together, the overall results were 76.0%, 72.5%, and 70.5% when diagnosis was conducted based on decision trees, binary logistic regression, and discriminant analysis respectively. The advantage of decision trees is the easiness of interpretation as well as the description and classification efficiency achieved with a simple segmentation of data.

4. Discussion

The technique of trees we have used in the present work is simple but powerful: each node is a relevant variable so that, in a subject problem, if a variable is greater or smaller than a threshold, then it goes for a branch or another and stops in the desired node, obviously the node with the highest accuracy. This technique is popular in what is called data mining. It has outperformed neural networks because the trees are able to explain what the networks cannot, as the latter factually work as a black box. Of course, when we compare this technique with the discriminant procedure of our previous work, we can see how the variables work in each case to distinguish a healthy control from a patient "in the blues". Whereas, in the discriminant analysis, the percentage of correctly classified patients with depression was of 85.12%, with the decision tree the percentage is 82.1%, indeed a very similar value.

The present results are significant in several analytical regards. Firstly, it is obvious that comparing with the previous results entropy *alone* is able to detect differences between patients and control subjects, while in the discriminant analysis such differences are detected by an ample set of variables. However, it is surprising that in the decision tree analysis the fifth plosive is once again the most discriminating factor between healthy subjects and depressed patients; a similar result was obtained in the discriminant analysis when the study was conducted with men only. Secondly, the current study shows that an individual suffers depression when the fifth plosive entropy is not relevant or has a low value. This result supports the relevance of the fifth plosive, suggesting as a surprising novelty the use of just the fifth plosive's entropy for the diagnosis, or more prudently its use as a complement of the results obtained from the other variables in the discriminant analysis. Nevertheless, the use of entropy in medical diagnosis is not new [35]. For example, a high value of entropy in the electroencephalography (EEG) of a patient, or a low value of entropy in the electrocardiography (ECG), predict a possible epileptic seizure [36] or a possible arrhythmia [37], respectively.

Regarding the biomedical interpretation, the present results throw further light on the possibility of specific detection of mental disorders. A number of new medical methods are being designed for early diagnosis in the most important mental pathologies and neurodegenerative diseases: new biochemical and molecular detectors, EEG, neuroimaging, ocular-macular exploration, pupillometry, exercise and gait analysis, equilibrium platforms, manual exercises, cognitive trials, memory tests, linguistic trials, *etc.* [27,35,38–41]. We think laughter could also be added to that list of biomedical explorations. The emotional–cognitive characteristics of laughter, where ample swaths of brain cortical areas as well as medial and cerebellar regions are involved, make for a promising model system in early diagnostics—looking for conspicuous alterations in entropy, energy and F_0, the variables where most of the "emotional code" of laughter is ensconced. Another important characteristic, not explored here, would concern the *timing* of laughter, where non-standard placement of laughter relative to topic boundaries may reveal failure to maintain engagement in dialogue [42,43]. The different pathological states would quite probably imprint their specific signature on all those variables and characteristics, although the decoding would not be easy. In addition, there may be methodological difficulties to establish the detection procedures, mostly at standardizing the video probes and the circumstances of social engagement—the social nature of laughter can never be overemphasized. Notwithstanding its interesting research content, making progress in this exploration may also contribute to enlivening and humanizing the environment surrounding the diagnosis and treatment of depression and other mental disorders. The present experience shows that patients participate with gusto in the laughing exercise.

From an evolutionary point of view, the results obtained are coherent with the current views on the acoustic expression of emotions and with their specific ontogenetic/phylogenetic development. There have been interesting debates on the nature of human emotions and the reliability of their acoustic detection, both in humans and in other primate and non-primate species [4,17,44–47]. It is relevant that the three essential variables statistically discriminated in our previous study (energy, entropy, and F_0) appear repeatedly in the different experimental studies. From another angle, it may be emphasized that our results are compatible with both the discrete states approach to emotions [48] and the continuous bi-dimensional approach [49]. In the former, the different emotional states would correspond with the different combinations of essential variables. While, in the latter, emotions (and laughter production) are represented in a continuum of two variables: *arousal* and *valence*, respectively meaning the level of neural excitation and the positive or negative connotation inherent to each emotion class. Most of the acoustic counterpart of *arousal* is conveyed by both energy and entropy (amplitude and dispersion of the frequency spectrum), while the excursions of F_0 and also a relative presence of entropy would correspond to *valence*.

Why is entropy so important in the acoustic manifestation of emotions as well as in the emission of laughter? The two reasons advanced in the Introduction have to be considered. On the emission side, recent studies corroborate the importance of order and disorder, of energy dispersion, in the production of acoustic signals [17,35,50,51]. There is a juvenile pattern of more entropic calls, which are progressively matured into well-formed calls, also influenced by the contact with adults [17]. Evolutionarily, higher entropy is related to poorer or more primitive control by neural circuits; however, at the same time, it attracts more attention by third parties and is more efficient as an emotional mover. In the human case, the neural circuit in charge of producing laughter's inarticulate sounds, partially the vagal system with its laryngeal nerve branch, has less controlling capabilities than the circuits in charge of spoken language (or contrived laughter for that matter); and something similar would happen with the rest of the physical phonatory–articulatory system involved [4,20,42]. Thus, spontaneous laughter would have higher entropic content respect to language, which is even higher in toddlers and infants—also in accordance with the higher arousal level that usually accompanies their laughter displays. Conversely, lower emotional engagement and lower arousal, as happens in depression patients, should be accompanied by both lower entropy and lower energy in the emitted signal, and that is precisely what our studies show.

On the reception side, the effect of laughter on the receiver conduces to a discussion on its nature as an honest signal. Given that it has a considerable social effect on the receiver side, it may be easily subject to manipulation and faked by the emitter. As pointed out [20], contrived laughter is relatively well distinguished from spontaneous laughter by means of a series of differences in duration, pitch, F_0, loudness, and entropy, and this is an aspect that has to be carefully considered in the case of depression. Quite probably, the depressed patient, with his/her lower arousal, is even "too honest" in the disclosure of this socially unwanted condition. Then, there appears a significant gender difference, as social conventions in most cultures penalize more the social evaluation of depressed males than of depressed females. Thus, depressed males suffer the full blunt of the social stigma, while females may feel less socially pressed and freer to express their depressed state or not. The gender aspects of depression include some other complexities derived from the different prevalence of the disorder, the different appreciation of humor between the sexes, and the differences involved in neuroanatomic–connectomic matters, as discussed in [30]. In any case, very clear indications of gender differences have surfaced in our two studies.

Finally, recent approaches to brain dynamics are relying on informational/entropic constructs. Following [18,19], the brain unifies its information processing by means of a distributed free-energy variable based on the coupling of excitation and inhibition, the informational entropy of which is maximized (optimized) in the ongoing search of adapting the sensory-motor states to the environmental demands. Given the mappings, gradients, circuit topologies, and self-organizing rhythms in the couplings between excitation and inhibition, the blind optimization of this brute "neural entropy" produces the outcome of well-fitted states. In the human context, laughter would have been co-opted as a generalized information-processing tool, a *finalizer* accompanying the higher-level cortical processing [52]. In some way, we laugh *abstractly*: when a significant neurodynamic constellation coding for some problematic circumstance suddenly vanishes, *i.e.*, when a relatively relevant behavioral problem becomes unexpectedly channeled in a positive way and vanishes as such problem. Laughter is then spontaneously produced by the subject to display his/her own behavioral competence in an instinctive way. Powerful neurodynamic, neuromolecular, and physiological resources have been internally mobilized without implying any extra computational–cognitive burden upon the subject's ongoing consciousness processes [30]. This role of laughter makes a lot of sense in the really complex social world that the "talkative" human brain has to confront, with a myriad of cognitive, behavioral, and relational problems. The conceptual–symbolic world of language is crucial in the making and breaking of social bonds, where emotional–relational problems may dramatically accumulate in extremely short periods of time [3,12]. When we laugh, the inner entropy generated is emitted to the outside, reflecting the occurring evolution of the neurodynamic processing gradients. Thus, the entropy of laughter is not only a useful biomedical resource; it may also be an amazing window to our most basic informational operations.

5. Conclusions

The present paper has explored the potential of a relevant variable of laughter's acoustic signature—entropy—in the detection of a widespread mental disorder, depression, as well as in gauging the severity of its diagnostic. By using laughter's entropy and by applying the decision trees procedure, it was possible to discriminate between patients and controls with 82.1% accuracy.

Potentially, laughter appears as a promising model system in early diagnostics, severity, and recovery course regarding important mental pathologies as well as neurodegenerative diseases. The variables herein explored (and some other characteristics) could be easily checked, and the methodology followed could also be effortlessly incorporated within the existing medical practices, in a more convivial and patient-friendly way. However, further studies are needed to ultimately establish these new kind of laughter-centered methods, so that they could be incorporated into the present stock of diagnostic/therapeutic tools.

As for the main limitations of the study: (i) the sample size is too reduced and may not be representative of the general population of depressed patients; (ii) the existing compilation of humorous videos is too general, irrespective of age, sex, mood, specific cultural backgrounds, *etc.*, and in some cases it may fail to produce laughter; (iii) although the conditions surrounding patient and control subjects are comfortable enough, it is not easy for them to feel at ease and laugh naturally when they know that they may be observed and that all their sounds are recorded; (iv) and finally, in the evaluation of the records, determining whether a laughter episode was suitable or not—"clean" enough—depended on personal inspection, not easily amenable to complete description by a rule system (although the procedure was the same for both patients and controls).

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