Challenges of Trustable AI and Added-Value on Health
B. Séroussi et al. (Eds.)

doi:10.3233/SHTI220506

Constructive Fuzzy Cognitive Map for Depression Severity Estimation

Georgia SOVATZIDI[a], Michael VASILAKAKIS, and Dimitris K. IAKOVIDIS[a,1]
[a]*Dept of Computer Science and Biomedical Informatics, Univ. of Thessaly, Greece*

Abstract. Depression is a common and serious medical disorder that negatively affects the mood and the emotions of people, especially adolescents. In this paper, a novel framework for automatically creating Fuzzy Cognitive Maps (FCMs) is proposed. It is applied for the estimation of the severity of depression among adolescents, based on their electroencephalogram (EEG). The introduced Constructive FCM (CFCM) utilizes features extracted by a Constructive Fuzzy Representation Model (CFRM), which conduces to detect in a more intuitive way the cause-and-effect relationships between the brain activity and depression. CFCM contributes to limiting the participation of experts, and the manual interventions in the traditional construction of FCMs, it provides an embedded mechanism for dimensionality reduction, and it constitutes an inherently interpretable approach to decision making, while being uncertainty-aware and simple to implement. The results of the experiments, using a recent publicly available dataset, demonstrate the effectiveness of the proposed framework and highlight its advantages.

Keywords. Fuzzy Cognitive Map, Fuzzy logic, Artificial Intelligence, Electroencephalogram (EEG), Interpretability, Depression.

1. Introduction

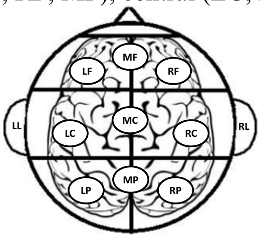
Clinical depression is a common mental disorder affecting more than 264 million people worldwide, according to the World Health Organization (1). The incidence of depression, like other related mood disorders, increases dramatically during the adolescence (2). Each adolescent may experience this disorder with different symptoms, such as emotional and cognitive signs, *e.g.*, sadness, stress, loss of interest and concentration.

Fuzzy Cognitive Maps (FCMs) consist a soft computing technique that has been used in many applications of several domains, including medicine (3). In general, the manual development of an FCM requires the participation of at least one specialist with experience. However, in some cases, no specialist may be available to help define an FCM, whereas it is difficult to manually design the model. In this paper, a novel framework for automatically creating FCMs is proposed, and is applied for depression severity estimation among adolescents. The introduced Constructive Fuzzy Cognitive Map (CFCM) utilizes features extracted using the recently proposed Constructive Fuzzy Representation Model (CFRM) (4). Specifically, CFRM detects the cause-and-effect relationships between the brain activity and the different states of depression, in an intuitive way, whereas it contributes to select the most informative features; thus, reducing the overall dimensionality of the problem under investigation.

[1] Corresponding Author, E-mail: diakovidis@uth.gr.

2. Material and Methods

To examine the brain, a segmentation of the EEG electrode positions into 11 regions was performed, based on (5). The electrodes were grouped into left, right, and midline frontal (LF, RF, MF), central (LC, RC, MC), and parietal (LP, RP, MP) regions (Figure 1).



1. Left Frontal (LF) {AF_3,F_1, F_3, F_5, F_7, FC_1, FC_3, FC_5,F_{p1}}
2. Left Central (LC) { C_1, C_3, C_5, CP_1, CP_3, CP_5 }
3. Left Parietal (LP) {P_1, P_3, P_5, P_7, PO_3, PO_5 ,PO_7 ,O_1}
4. Left Lateral (LL) { FT_7, T_7, TP_7 }
5. Midline Frontal (MF) { F_z, FC_z,F_{pz} }
6. Midline Central (MC) { CP_z, C_z }
7. Midline Parietal (MP) { P_z, PO_z ,O_z }
8. Right Frontal (RF) { AF_4,F_2, F_4 , F_6, F_8, FC_2, FC_4, FC_6 , F_{p2}}
9. Right Central (RC) { C_2, C_4, C_6, CP_2, CP_4, CP_6 }
10. Right Parietal (RP) { P_2, P_4, P_6, P_8, PO_4, PO_6 , PO_8, O_2 }
11. Right Lateral (RL) { FT_8, T_8, TP_8 }

Figure 1. Segmentation of the electrical activity of the brain into 11 regions.

2.1 Constructive Fuzzy Representation of EEG Signals

Let us consider a feature vector $F^u_{r,\lambda} = \left(f^u_1, f^u_2, \ldots, f^u_{N_r}\right)$, where u represents the wave types and $\lambda = 1,2,\ldots,\Lambda$ is a class identifier corresponding to the degree of depression, *e.g.,* minimal depression; $r = 1,2,\ldots,R$ are the examined brain regions, whereas N_r represents the number of EEG electrodes in the region *r* (Figure 1). Specifically, based on (5), a total number of $R = 11$ brain regions were used for the experiments. CFRM (4) is utilized to construct fuzzy sets and select the most informative features, which in our case correspond to the examined electrodes. The application of CFRM proceeds in 4 steps (Figure 2): a) it applies a clustering algorithm to group $F^u_{r,\lambda}$ into a set of M clusters with $M < K_\lambda$, where K_λ is the number of patients with $\lambda = 1,2,\ldots,\Lambda$; b) The resulting centroids $q_m, m = 1,\ldots,M$ and standard deviations $s_m, m = 1,\ldots,M$ of the clusters are used to define the fuzzy sets; c) These fuzzy sets are then aggregated using the fuzzy union operation, resulting into new fuzzy sets, each of which corresponds to a feature f^u_n, n=1,2,…, N_r, and it has a membership function $\mu_\lambda(f^u_{k,n})$, k =1,2,…, K_λ; d) All the membership functions $\mu_\lambda(f^u_{k,n})$, k=1,2,…, K_λ , n=1,2,…, N_r , for $\lambda = 1,2,\ldots,\Lambda$, are evaluated with respect to their overlap, and the features that correspond to fuzzy sets with highly overlapping membership functions are considered redundant and they are discarded. The application of this methodology on EEG features (6), showed that the delta and beta waves of all the examined electrodes, as well as those belonging to the lateral regions, *i.e.*, LL, RL, are redundant and they were discarded. Therefore, a total of 9 out of the 11 brain regions are considered for the experiments of this paper. In the sequel, for a given patient *K* the selected features $f^u_{K,n}, n = 1,2,\ldots,N'_r$ $(N'_r \leq N_r), r = 1,2,\ldots,9$ are provided as input to the membership functions of the derived fuzzy sets, *i.e.*, the values $\mu_\lambda\left(f^u_{K,n}\right), n = 1,2,\ldots,N'_r, \lambda = 1,2,\ldots,\Lambda$, are calculated. Considering

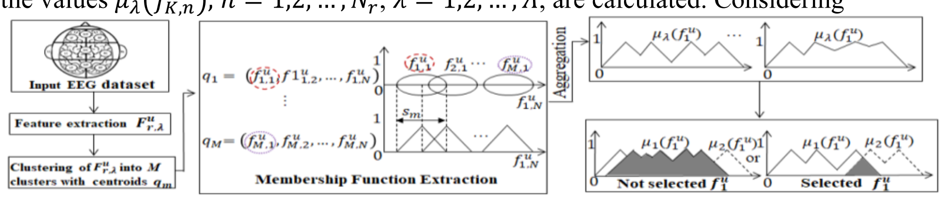


Figure 2. Overview of the Constructive Fuzzy Representation Model

$M_{K,r} = \max\left(\left(\mu_1\left(f_{K,n}^u\right), \mu_2\left(f_{K,n}^u\right), \mu_3\left(f_{K,n}^u\right)\right)\right)$ and $m_{K,r} = \left(\mu_1\left(f_{K,n}^u\right), \mu_2\left(f_{K,n}^u\right), \mu_3\left(f_{K,n}^u\right)\right)$, where $M_{K,r}$ corresponds to the maximum membership value of the selected fuzzy set $m_{K,r}$, the initial values A_r of the nodes of the CFCM are calculated by Eq.(1), which facilitates normalization purposes:

$$A_{K,r} = \begin{cases} 0 \leq M_{K,r} \cdot \frac{1}{3} \leq 0.33, & if\ m_{K,r} = 1 \\ 0.33 \leq M_{K,r} \cdot \frac{2}{3} \leq 0.66, & if\ m_{K,r} = 2 \\ 0.66 \leq M_{K,r} \leq 1, & if\ m_{K,r} = 3 \end{cases} \tag{1}$$

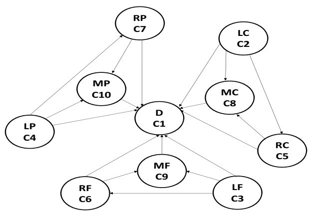
2.2 Constructive FCM

FCMs represent knowledge through concepts and directed, weighted edges between them (7). An FCM is defined as an ordered pair $< C, W >$, where C is the set of concepts and W is a quadratic matrix consisting of w_{ij} weights that determine the relationships among the concepts. The concept values of nodes $C = C_1, C_2, \ldots, C_n$, where *n* is the number of concepts, represent the state vector $A = \{A_r\}$.

The proposed CFCM is an FCM that is automatically constructed, given a set of initial concepts and a respective training dataset. In this study, a total of 11 initial concepts, representing the brain regions illustrated in Figure 1, were considered. The CRFM methodology is applied, and as described in section 2.2, from the 11 initial brain regions, only 9 of them are selected, and used for the construction of the CFCM model. Figure 3(a) illustrates the selected concepts of CFCM; C_1=Depression (D), which is the output concept, and the input concepts C_2= Left Central (LC), C_3= Left Frontal (LF), C_4= Left Parietal (LP), C_5= Right Central (RC), C_6= Right Frontal (RF), C_7= Right Parietal (RP), C_8= Midline Central (MC), C_9= Midline Frontal (MF) and C_{10}= Midline Parietal (MP). To estimate the weight matrix of CFCM (Figure 3(b)) the causal relationships between the concepts are examined. Initially, the average value $\overline{A_{r|\lambda}}$, $r = 1,2, \ldots, 9$, is obtained from all patients belonging to class λ in the training set, *i.e.*, the average of $A_{k,r}$, k=1,2,…, K_λ, for $\lambda = 1,2, \ldots, \Lambda$. This average value characterizes the brain activity of the respective depression state *c*. Then, the influence between two concepts C_i and C_j, $i \neq j$, which represent the brain activity in two brain regions *i* and *j*, can be defined with respect to the differences observed in the brain activity in all cases of depression, as $E_{i \to j}^{\lambda_2, \lambda_1} = (\overline{A_{i|\lambda_2}} + \overline{A_{j|\lambda_2}} - \overline{A_{i|\lambda_1}} - \overline{A_{j|\lambda_1}}) / (\overline{A_{i|\lambda_2}} + \overline{A_{j|\lambda_2}} + \overline{A_{i|\lambda_1}} + \overline{A_{j|\lambda_1}})$, where $i, j = 1,2, \ldots, 9$, and $\lambda_1, \lambda_2 = 1,2, \ldots, \Lambda, \lambda_1 < \lambda_2$. The computed $E_{i \to j}^{\lambda_2, \lambda_1}$ are subsequently fuzzified using fuzzy sets defined in $[-2 \cdot \min(E_{i \to j}), 2 \cdot \max(E_{i \to j})]$ (Figure 3(c)). The fuzzy set in which $E_{i \to j}^{\lambda_2, \lambda_1}$ exhibit the maximum membership, is selected to linguistically represent the respective influence, using one of the three linguistic values, "negative", "neutral" and "positive". The final weight of each edge $i \to j$ is calculated as the center of gravity of the membership function obtained by the aggregation (using the algebraic sum) of the respective membership functions of $E_{i \to j}^{\lambda_2, \lambda_1}$. For a test case of a patient with unknown severity of depression, the developed CFCM iteratively calculates its state until convergence, for T iterations, according to the equation $A_i^{t+1} = g\left(A_i^t + \sum_{j=1, j \neq i}^{n} w_{ji} A_j^t\right)$, where $t = 1 \ldots., T$ is the iteration, w_{ji} is the weight matrix of the edge connecting C_j to C_i, and g is the log sigmoid function. The values of the initial state vector $A^0 = (A_1^0, \ldots, A_n^0)$ are estimated by Eq.(1) using EEG measurements from the test patient.

2.3 Data Description and Preprocessing

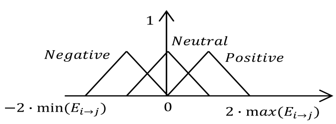
The dataset used in the experiments provides behavioral and electrophysiological information during eyes-closed and -open sessions over 60 electrode sites from 85 adolescents with minimal, mild, and moderate depression (6). In addition, the dataset was smoothed and averaged over five wave types: delta (1–4 Hz), theta (4–8 Hz), lower alpha (8–10 Hz), upper alpha (10–12 Hz), and beta (13–30 Hz). The absolute power of the EEG for five frequency bands was considered, resulting in a total of 5×60=300 EEG features. A total of 10 variations of this dataset was created, by following a 10-fold cross validation of the patient samples into non-overlapping training and test subsets.



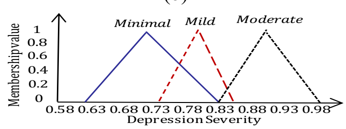
(a)

$$w_{ij}=\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -0.23 & 0 & 0 & 0 & -0.33 & 0 & 0 & -0.33 & 0 & 0 \\ 0.48 & 0 & 0 & 0 & 0 & 0.23 & 0 & 0 & 0.24 & 0 \\ -0.01 & 0 & 0 & 0 & 0 & 0 & -0.32 & 0 & 0 & -0.13 \\ 0.60 & 0 & 0 & 0 & 0 & 0 & 0 & -0.29 & 0 & 0 \\ 0.11 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.13 & 0 \\ 0.55 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.05 \\ 0.19 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.57 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -0.21 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

(b)



(c)



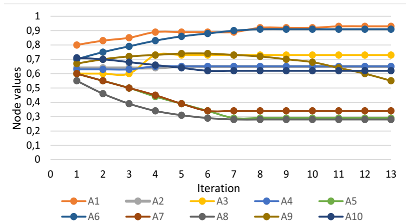
(d)

Figure 3. (a) CFCM structure. (b) Weight matrix of CFCM. (c) Membership functions of the influences between the CFCM concepts. (d) Membership functions for depression severity (output concept C_1).

3. Depression Severity Evaluation

As an example of the test phase described in the previous section, patient 76 of the available dataset was randomly selected. Using Eq.(1) the initial state vector $A^0 = (0, 0.66, 1, 0.66, 0.66, 0.64, 0.66, 0.64, 0.58, 0.97)$ is calculated. CFCM converged to a steady state after 13 iterations, using the weight matrix of Figure 3(b). The resulting state vector was $A^{13} = (\mathbf{0.93}, 0.73, 0.65, 0.09, 0.97, 0.15, 0.58, 0.55, \ 0.36)$ which shows that the patient has a "Moderate" depression equal to 0.93, taking into consideration Figure 3(d). According to A^{13}, a depressive patient has a more intense electrical activity on the left than on the right hemisphere of the brain. This can be inferred from the fact that $LC = 0.65 < RC = 0.09$, $LF = 0.73 < 0.97$ and $LP = 0.65 < RP = 0.10$. The evolution of the concept values, during the iterations, is illustrated in Figure 4(a).

Considering that this dataset has not been previously used in a classification context, we evaluated its decision making performance in comparison to four well-known classifiers (4). As it can be observed from Figure 4(b), CFCM provides higher or comparable results with significantly lower dimensionality (Dim), to the compared classifiers. Also, CFCM provides outcomes that are easily interpretable, based on its graph, explaining causal relationships of the involved concepts.



(a)

Classifier	Accuracy	Precision	Recall	Dim
SVM	0.64	0.69	0.62	300
k-NN	0.56	0.59	0.55	300
Naïve Bayes	0.58	0.65	0.58	300
CFRM	0.64	0.69	0.62	62
CFCM	**0.65**	**0.75**	**0.65**	**9**

(b)

Figure 4. (a) Values of CFCM nodes for a depressive patient. (b) Comparisons of CFCM with other classifiers.

4. Conclusion

In this paper, a novel framework for automatically constructing an FCM was proposed, with application to the depression severity among adolescents, based on their EEG. The experiments demonstrated the effectiveness of the introduced CFCM model, as it succeeded in identifying which brain regions were most associated with depression, while automatically detecting the interconnections between them. CFCM is capable of providing easily interpretable results, while being aware of uncertainty, and it is simple to implement. Future work includes further investigation of the proposed framework, using different types of membership functions and its application on different contexts.

Acknowledgment

We acknowledge support of this work by the project “Smart Tourist” (MIS 5047243) which is implemented under the Action “Reinforcement of the Research and Innovation Infrastructure”, funded by the Operational Program "Competitiveness, Entrepreneurship and Innovation" (NSRF 2014-2020) and co-financed by Greece and the European Union (European Regional Development Fund).

References

1. World Health Organization (WHO), others. Depression and other common mental disorders: global health estimates. Document, World Health Organization; 2017.
2. Field T, Miguel D, Sanders C. Adolescent depression and risk factors. Adolescence. Libra Publishers Incorporated; 2001;36(143):491.
3. Amirkhani A, Papageorgiou EI, Mohseni A, Mosavi MR. A review of fuzzy cognitive maps in medicine: Taxonomy, methods, and applications. Computer methods and programs in biomedicine. Elsevier; 2017;142:129–145.
4. Vasilakakis MD, Iakovidis DK, Koulaouzidis G. A Constructive Fuzzy Representation Model for Heart Data Classification. Public Health and Informatics. IOS Press; 2021. p. 13–17.
5. Kielar A, Joanisse MF. Graded effects of regularity in language revealed by N400 indices of morphological priming. Journal of cognitive neuroscience. MIT Press One Rogers Street, Cambridge, MA 02142-1209, USA journals-info …; 2010;22(7):1373–1398.
6. Rachamanee S, Wongupparaj P. Resting-state EEG datasets of adolescents with mild, minimal, and moderate depression. BMC Research Notes. Springer; 2021;14(1):1–3.
7. Kosko B. Fuzzy cognitive maps. International journal of man-machine studies. Els.; 1986;24(1):65–75.