Biomedical Engineering

Fuzzy C-mean, Reliable clustering for EMG and EEG

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Abstract:	Fuzzy C-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. The clustering of human neuromuscular motion and disease is of scientific concern making an accurate diagnosis. The current study focused on clustering the chaotic EEG patterns of alcoholic and non-alcholic individuals using FCM. The clusters were then examined to detect EMG signals of the hands that are affected and unaffected by stroke. An acceptable classification was determined for both types of biosignal clustering.
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Fuzzy C-mean, Reliable clustering for EMG and EEG

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Abstract: Fuzzy C-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. The clustering of human neuromuscular motion and disease is of scientific concern making an accurate diagnosis. The current study focused on clustering the chaotic EEG patterns of alcoholic and non-alcholic individuals using FCM. The clusters were then examined to detect EMG signals of the hands that are affected and unaffected by stroke. An acceptable classification was determined for both types of biosignal clustering.

Keywords: EEG signal, Fuzzy C-means cluster, Alcoholic pattern detection, EMG signals

Introduction:

Fuzzy C-Means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method was developed by Dunn [1] and improved upon by Bezdek [2]. This clustering approach is frequently used in signal and image processing [3]. Clustering of human neuromuscular diseases is of concern to scientists. The current study applied fuzzy C-mean classifiers to examine the power of clustering EEG and EMG datasets for two set of bio-signals.

Previous studies have used FCM to classify cardiac arrhythmia [4], characterize ECG signals based on blind source separation [5], used unsupervised fuzzy C-means clustering for recognition [6], also in the field of EEG signal studies, a fuzzy-based classifiers in EEGs and fuzzy logic has been used to classify sleep EEGs [7]. Adaptive neuro-fuzzy inference system for classification of EEG signals by wavelet coefficients in [8], Diagnosis and Classification of Epilepsy Risk Levels from EEG Signals by Using Fuzzy Techniques [9], Classification and Analysis of EEG Brain Signals for Finding Epilepsy Risk Levels by Using SVM [10], and performance analysis of patient specific eleman-chaotic optmazation model for fuzzy baised ephilephsy risk level classification from EEG signal [11]. For EMG data analyses and classifying it has been a long research back ground like Fuzzy Control of EMG Based Movement classification with Six Degree of Freedom[12] , Fuzzy Logic and Probabilistic Neural Network for EMG Classification [13], Classification of EMG based Diseases using Fuzzy Logic at Second Level[14]. A novel feature extraction method based on fuzzy entropy [15] , and Intention detection using a neuro-fuzzy EMG classifier are some of many [16]. The present study used fuzzy classifiers to visually recognize and

classify alcoholic from non-alcoholic cases and then used the FCM classifiers to recognize patients who had been affected and not affected by stroke from their EMG signals.

Embedding (Reconstruction) Spaces:

The time series data of a bio-signal like EEG or EMG was used to create a multidimensional embedding (reconstruction) space by two-dimensional (2D) (the x (t) signal in x axial and delay shifting of the x (t) in y axial). If the embedding space is created properly, the behavior of the signals in this embedding space will have the same structure.Also, Dynamics that characterize the actual signal in full multidimensional state space for a system sometimes shows hidden features that cannot be seen in a time series alone. The evolution of the signal in embedding space mirrors the behavior of the actual signal in the full state space.

The use of a trajectory time series to create an embedding space to characterize nonlinear dynamic systems was suggested by Packard et al. [17]. To observe how an embedding space is created, a series of x values for the dynamic system were recorded. The series of x and y values are used to reconstruct the behavior of the time series in 2D by grouping the values to form vectors. The x vector is the $X(t)$ value and the y vector is $X(t+d)$ in which d as the delay chosen to cover all characteristics of the time series is extracted by the mutual information method [18]. The present study showed all hidden characteristics of the EEG and EMG signals by embedding their time series in 2D and examining the FCM clusters on the vectors.

Mutual information:

The method of "mutual information" (MI) is a way to determine useful delay coordinates for plotting embedding space. The idea of delay

coordinates is basic. If one feature from a time series signal can be shown, $X(t)$, and should be reconstructed in a higher-dimensional space as $(X(t),X(t+T),...,X(t+nT))$ to create a $(n+1)$ dimensional vector. It is crucial to choose a good value for delay (T). If T is too short, then $X(t)$ is will be similar to $X(t+T)$. If the T is too long, then the values will be independent and no information can be extract from the plot. The MI method for finding a delay was proposed by Gwinn [19]. The MI method was used herein to create a delay of five steps (T=5 in $X(t+T)$) in both embedded EEG and EMG signals in order to use the best T.

Fuzzy C-Mean Cluster:

Fuzzy clustering is also called soft clustering and is a form in which each data set can belong to more than one cluster. Clustering or cluster analysis involves identifying data points to clusters called buckets, or homogeneous classes, such that points in the same group are as similar as possible, while items belonging to different groups are as dissimilar as possible. Clusters are recognized through similarity measures that cover distance, connectivity and intensity. Different similarity measures might be chosen based on the data. The algorithm works by assigning a membership to each data set corresponding to each group center on the basis of distance between the cluster center and the data set.

EEG Time Series and Simulation Results of Clustering by FCM:

Studies have shown that changes occur in the hemispheres of the brains of alcoholics [20, 21]. The CPZ and CP5 (EEG standards) were chosen to test for differences between the brains of the alcoholic and non-alcoholic control cases and classify them using FCM. Both the

control and test cases were male students: one 28 years old and the other 25 years old. The alcoholic reported drinking 5-10 alcholic drinks a day. Figure 2 shows the 2D embedding reconstruction CPZ in the 5-step delay gained by the MI method for both the alcoholic and the control case.

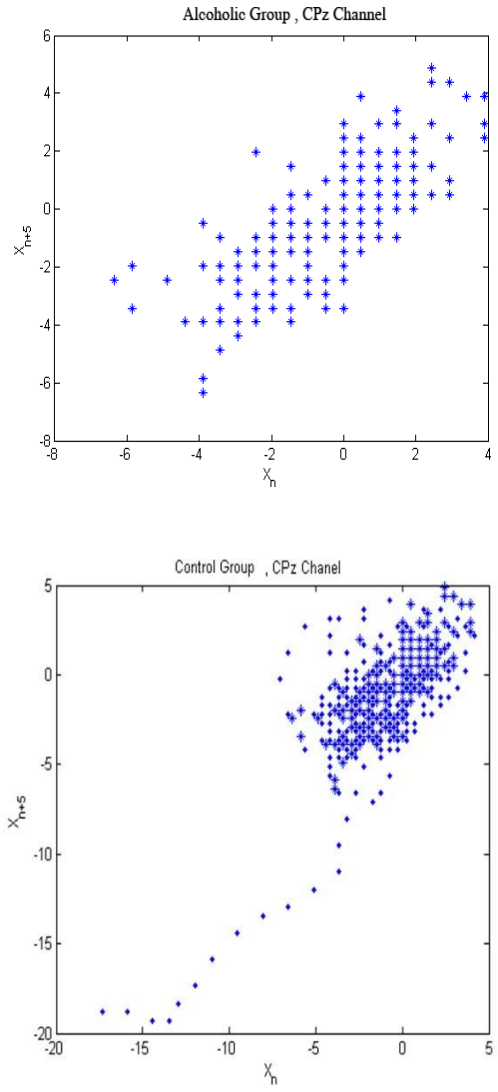

Figure 2. 2D embedding reconstruction by CPZ with 5-step delay gained by MI (alcoholic and the control case).

Figure 3 shows the CPZ classification by FCM in two embedding spaces (alcoholic and control case).

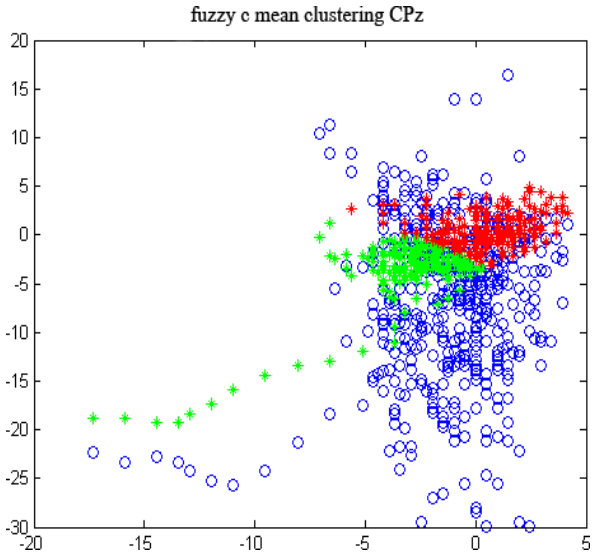

Figure 3. CPZ classification by FCM in two embedding spaces (alcoholic and the controlcase).

Figure 4 shows the CP5 2D embedding reconstruction by the 5-step delay gained by the MI method for both alcoholic and the control case.

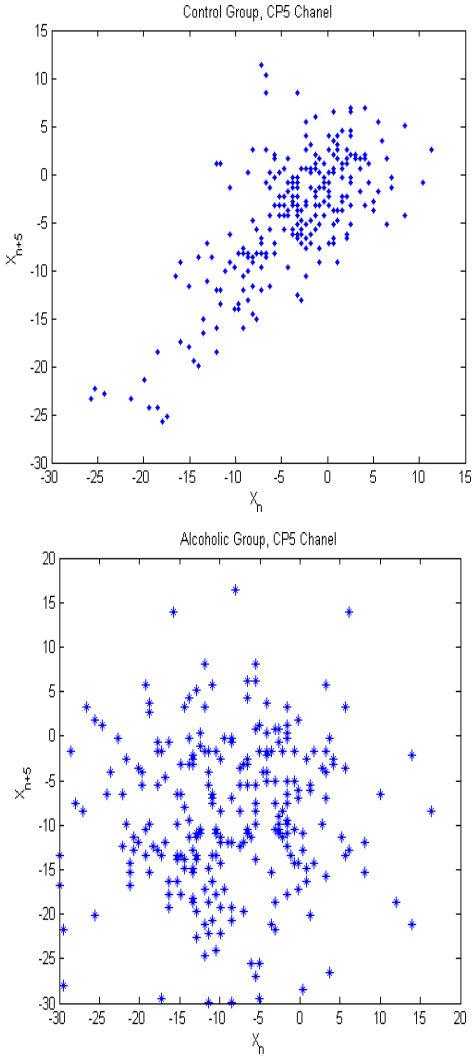

Figure 4. 2D CP5 embedding reconstruction with 5-step delay gained by MI (alcoholic and the control case).

Figure 5 shows the CP5 classification by FCM for two embedding spaces (alcoholic and the control case).

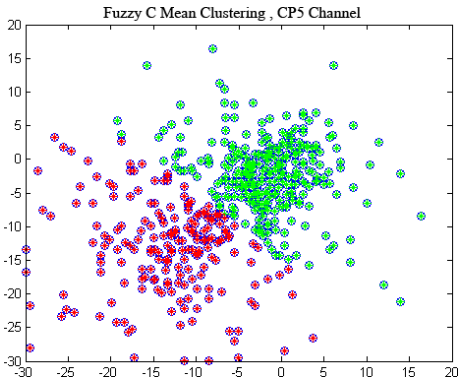

Figure 5. CP5 classification by FCM for two embedding spaces (alcoholic and the control case).

As seen, both embedding spaces and clustering can be distinguished completely by CP5.

Simulation results for EMG :

The EMG signals used were from affected and unaffected (control) stroke patients. The EMG records of the flexor carpi ulnaris (FCU) and flexor carpi radialis (FCR) were embedded in 2D using T=5 gained by mutual information as shown in Figure 6. Figure 7 shows the FCM classification of FCU and FCR in the affected and unaffected stroke cases.

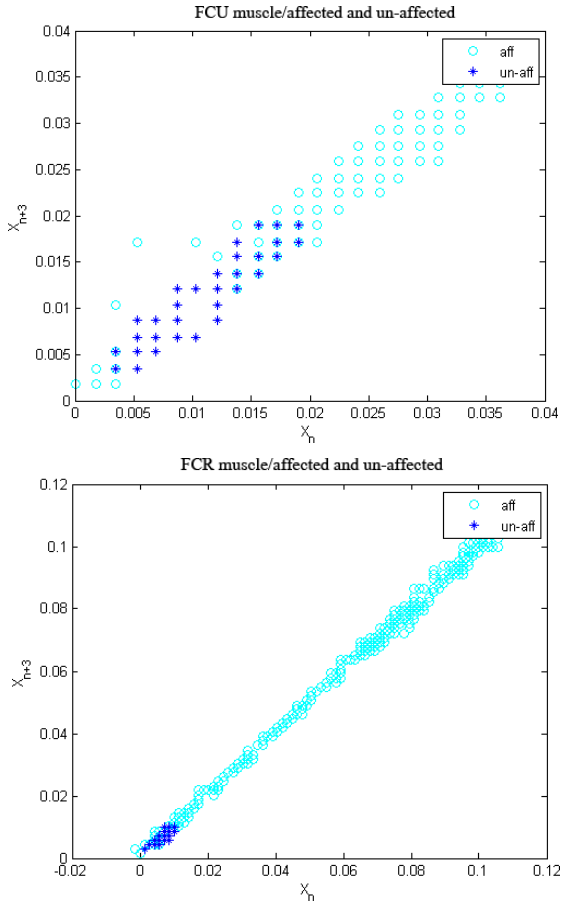

Figure 6. FCU and FCR for affected and unaffected stroke patients.

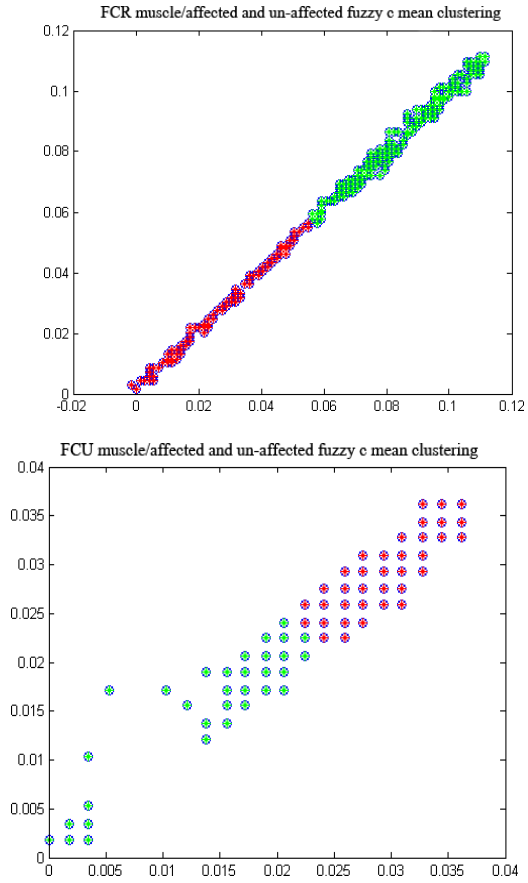

Figure 7. FCM classification of FCU and FCR for affected and unaffected stroke cases demonstrating good classification.

Conclusion:

The results show that both EEG and EMG signal classification of the FCM showed acceptable performance. In CPZ, better recognition was demonstrated when compare to CP5. It is shown that FCU and FCR are reliable classifiers. Embedding features in 2D classification was done properly, future research will endeavor to

develop the features in three dimension space and also by more complete databaise.

Ackonoledgment:

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Refrences:

[1] J. C. Dunn (1973): "A Fuzzy Relative of the ISODATA Process and Its Use in Detecting Compact Well-Separated Clusters", Journal of Cybernetics 3: 32-57

[2]J. C. Bezdek (1981): "Pattern Recognition with Fuzzy Objective Function Algoritms", Plenum Press, New York

[3] Cai W., Chen S. and Zhang D., "Fast and robust fuzzy c-means clustering algorithms incorporating local in formation for image segmentation", Pattern Recognition, Vol. 40, pp. 825–838, March, 2007.

[4] FUZZY C-MEANS CLUSTERING, NEURAL NETWORK, WT, AND HRV FOR CLASSIFICATION OF CARDIAC ARRHYTHMIA , A. Dallali, A. Kachouri and M. Samet, Journal of Engineering and Applied Sciences, VOL. 6, NO. 10, OCTOBER 2011

[5] Owis M. I., Youssef A.-B. M. and Kadah Y. M. 2002. Characterization of ECG signals based on blind source separation. Medical and Biological Engineering and Computing. 40: 557-564

[6] UNSUPERVISED FUZZY C-MEANS CLUSTERING FOR MOTOR IMAGERY EEG RECOGNITION , Wei-Yen Hsu, et all , nternational Journal of Innovative Computing, Information and Control, Volume 7, , Number 8, August 2011

[7] Sleep EEG Classification Using Fuzzy Logic , Chetna Nagpal, Dr PK Upadhyay, **International Journal of Recent Development in Engineering and Technology** , Vol. 6 (3) , 2015, 2031-2034

[8] Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients, Inan Gu¨ler, Elif Derya U¨ beyli, Journal of Neuroscience Methods , (2005)

[9] Diagnosis and Classification of Epilepsy Risk Levels from EEG Signals Using Fuzzy Aggregation Techniques,Dr. (Mrs.) R.Sukanesh, R. Harikumar, Engineering Letters,2007

[10] Classification and Analysis of EEG Brain Signals for Finding Epilepsy Risk LevelsUsing SVM , Sasikumar Gurumurthy and B.K. Tripathy, World Applied Sciences Journal 33 (4): 631-639, 2015

[11] PERFORMANCE ANALYSIS OF PATIENT SPECIFIC ELMAN-CHAOTIC OPTIMIZATION MODEL FOR FUZZY BASED EPILEPSY RISK LEVEL CLASSIFICATION FROM EEG SIGNALS , Dr.R.HariKumar, T.Vijayakumar, INTERNATIONAL JOURNAL ON SMART SENSING AND INTELLIGENT SYSTEMS, VOL. 2, NO. 4, DECEMBER 2009

[12] Fuzzy Control of EMG Based Movement lassification with Six Degree of Freedom, Chanchal Garg, Yogendra narayan, Ram murat singh, Dr. Lini Mathew, Inte rnational Journal of Engineering Technology, Management and Applied Sciences, July 2015, Volume 3, Issue 7, ISSN 2349-4476

[13] **Fuzzy Logic and Probabilistic Neural Network for EMG Classification A Comparitive Study,** Shalu George K., K S Sivanandan, K P Mohandas , International Journal of Engineering Research & Technology , vol1, 2015

[14] Classification of EMG based Diseases using Fuzzy Logic at Second Level, Babita Pandey and henna , International Journal of Computer Applications (0975 –

8887) Volume 91 – No.3, April 2014

[15] Khushaba RN, Al-Jumaily A, Al-Ani, “A. Novel feature extraction method based on fuzzy entropy and wavelet packet transform for myoelectric Control,” 2007 Int Symp Commun Inf Technol., pp. 352– 357, 2007.

[16] S.E. Hussein, M.H. Granat, Intention detection using a neuro-fuzzy EMG classifier, IEEE Engineering in Medicine and Biology November/December (2002) 123–129.

[17] N. H. Packard, J. P. Crutchfield, J. D. Farmer, and R. S. Shaw, "Geometry from a Time Series," **Phys. Rev. Lett.** 45,712-15 (1980).

[18] Chaos and nonlinear dynamics: an introduction for scientists and engineers, RC Hilborn ‐2000

[19] E. G. Gwinn and R. M. Westervelt, "Fractal Basin Boundaries and Intermittency in the Driven Damped Pendulum," Phys. Rev. A 33,4143-55 (1986).

[20] Oscar-Berman M, Marinkovi K (2007) Alcohol: effects on neurobehavioral functions and the brain. Neuropsychol Rev 17(3):239–257

[21] Analysis of alcoholic EEG signals based on horizontal visibility graph entropy, Guohun Zhu, Yan Li, Peng (Paul) Wen, Shuaifang Wang, Brain Informatics, December 2014, Volume 1, Issue 1, pp 19–25

Figure(s)

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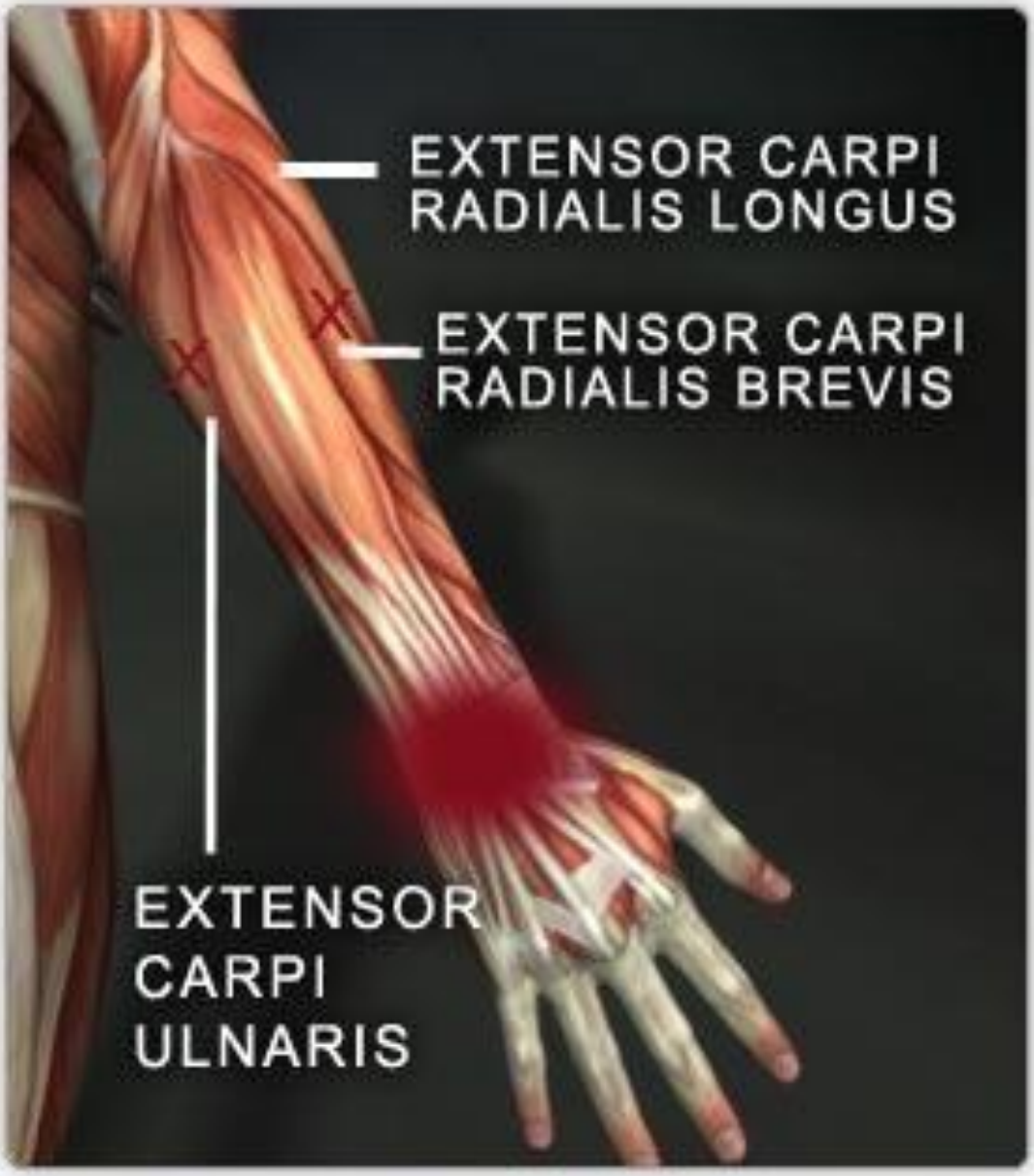
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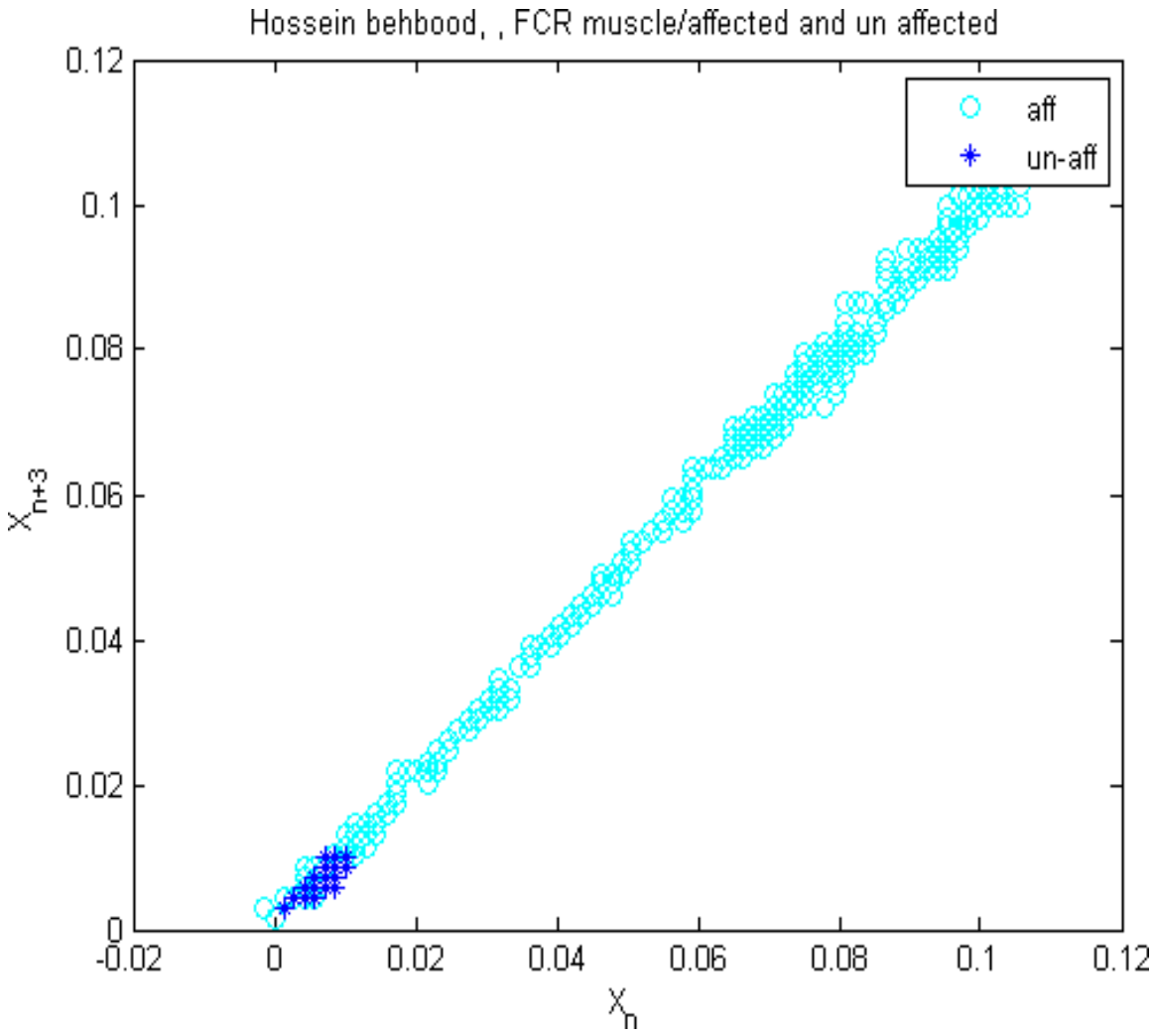
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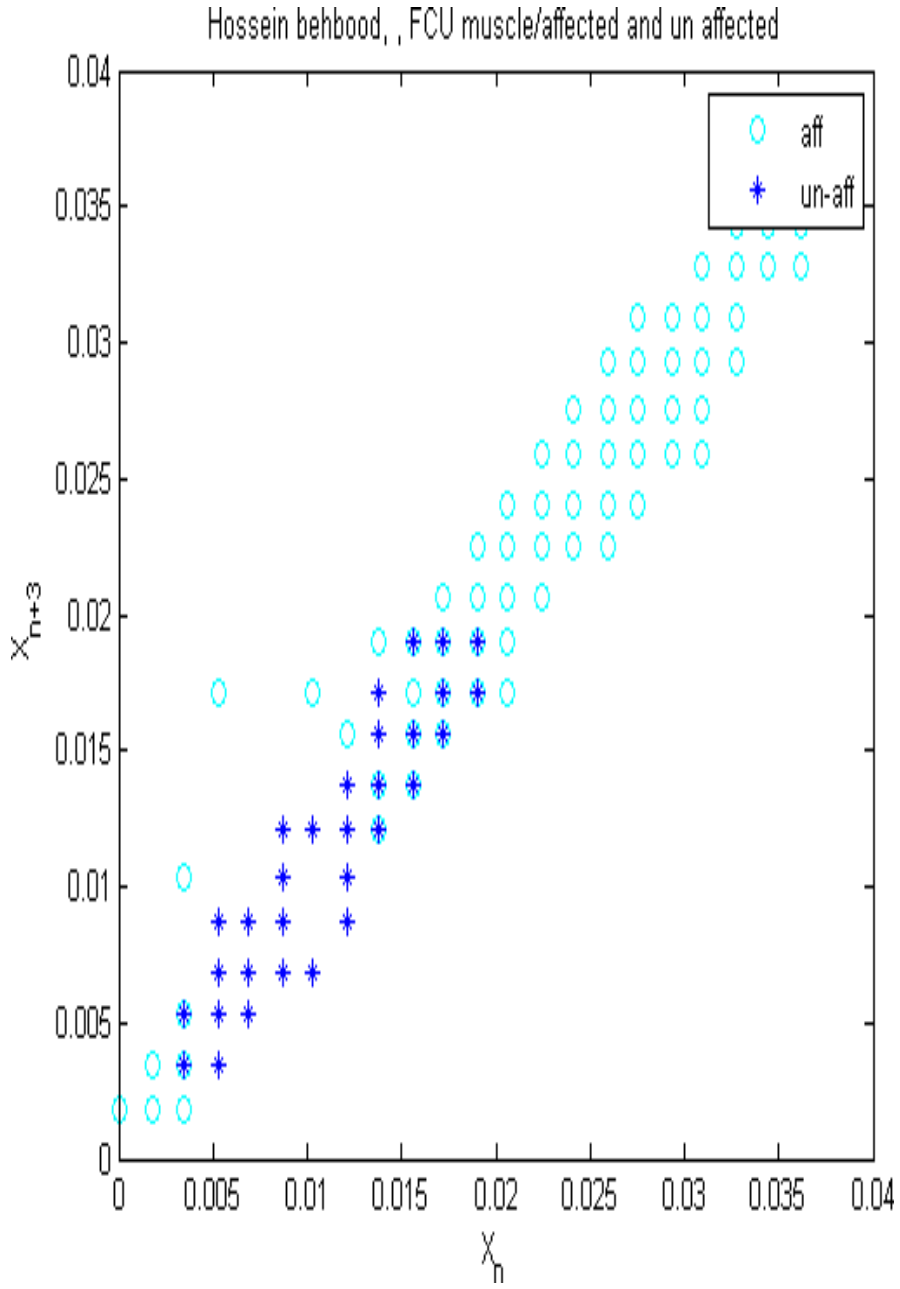
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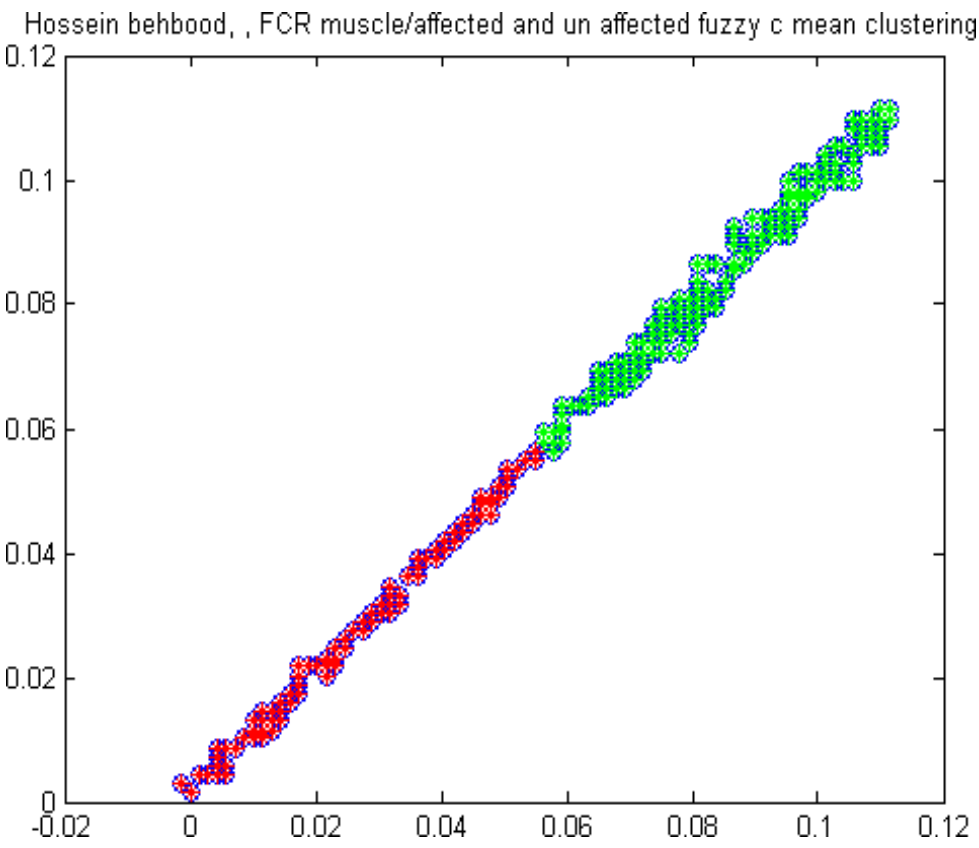
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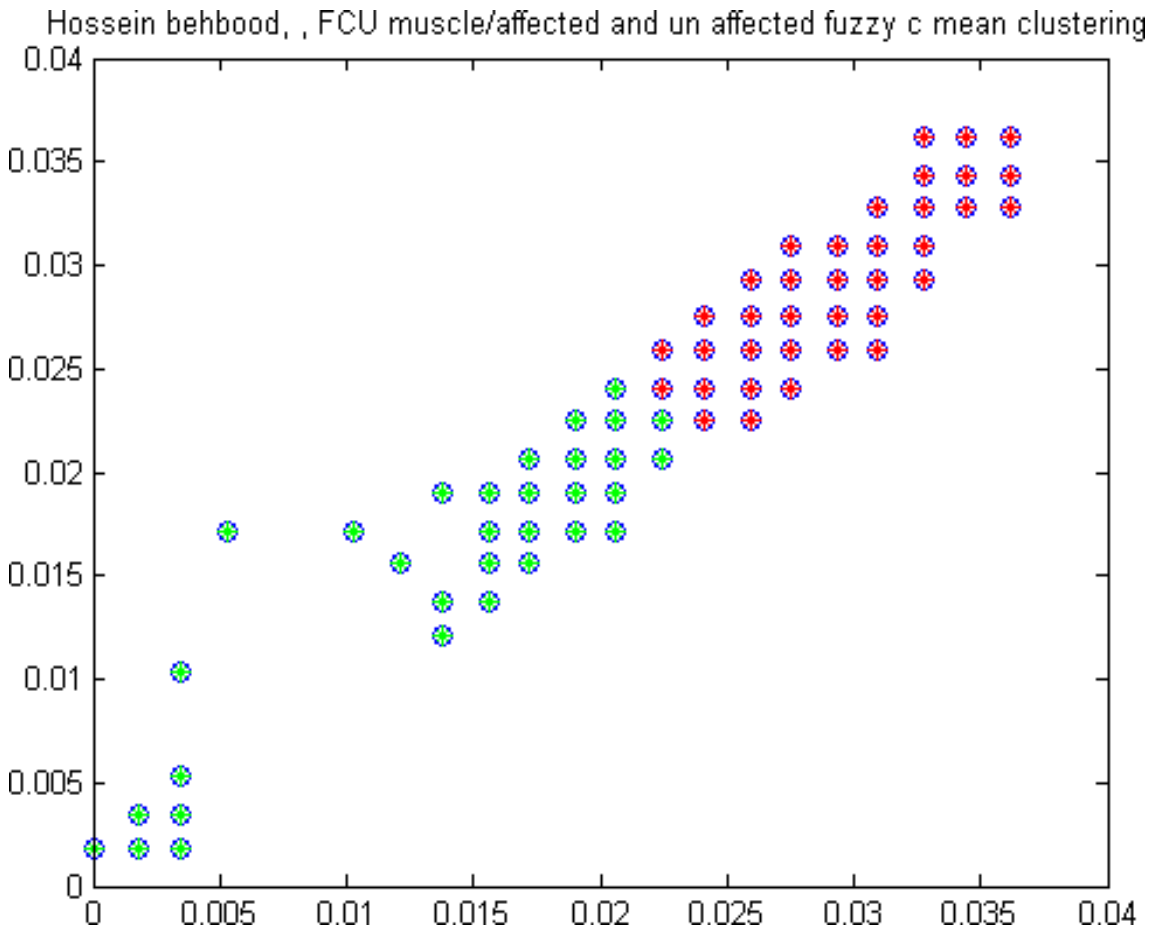
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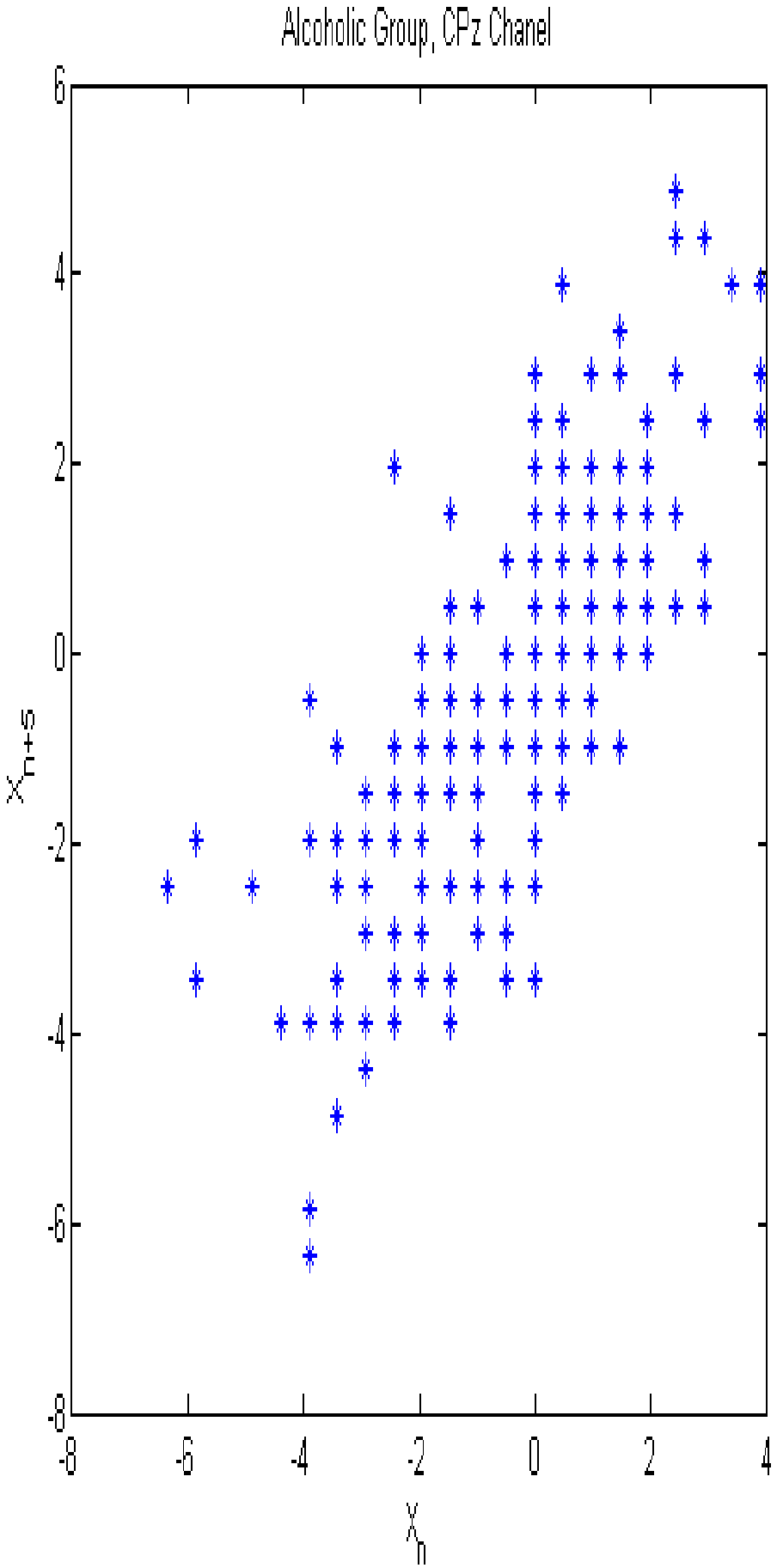
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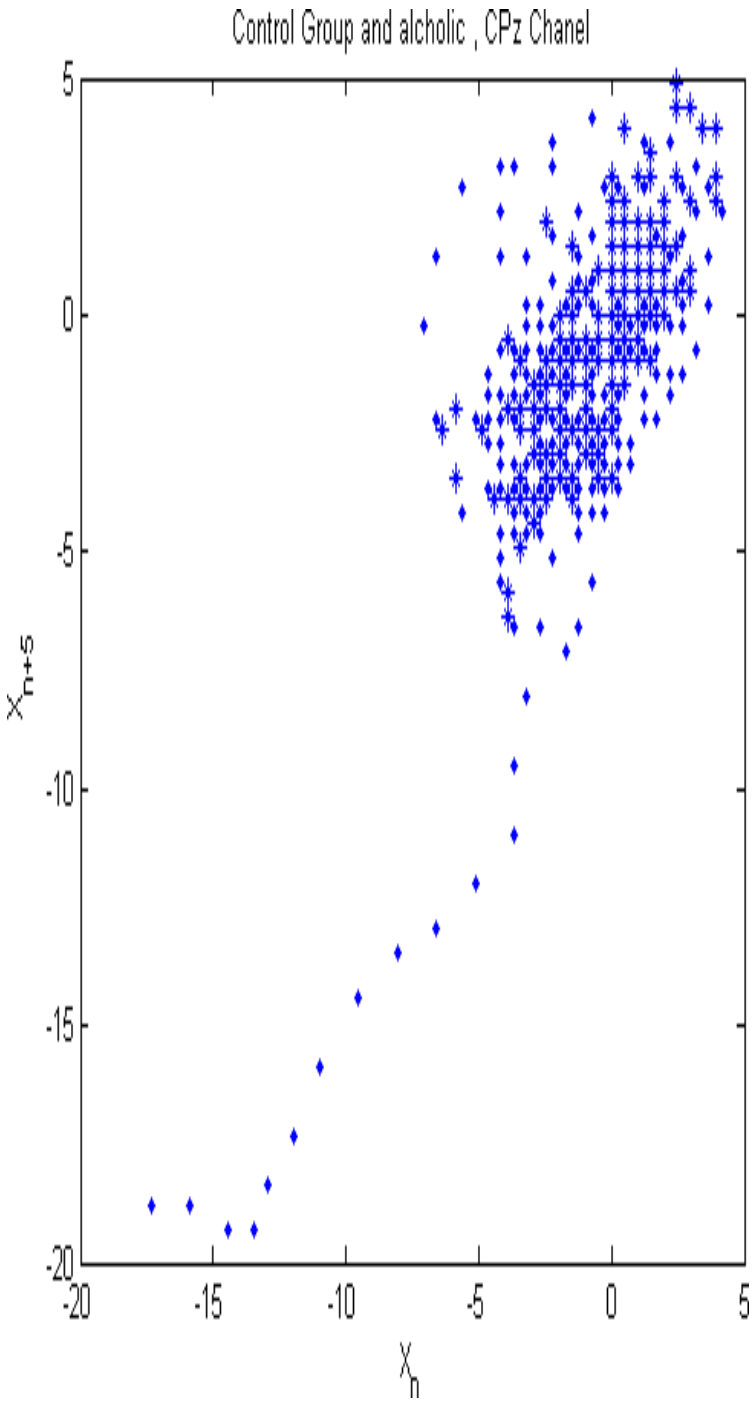
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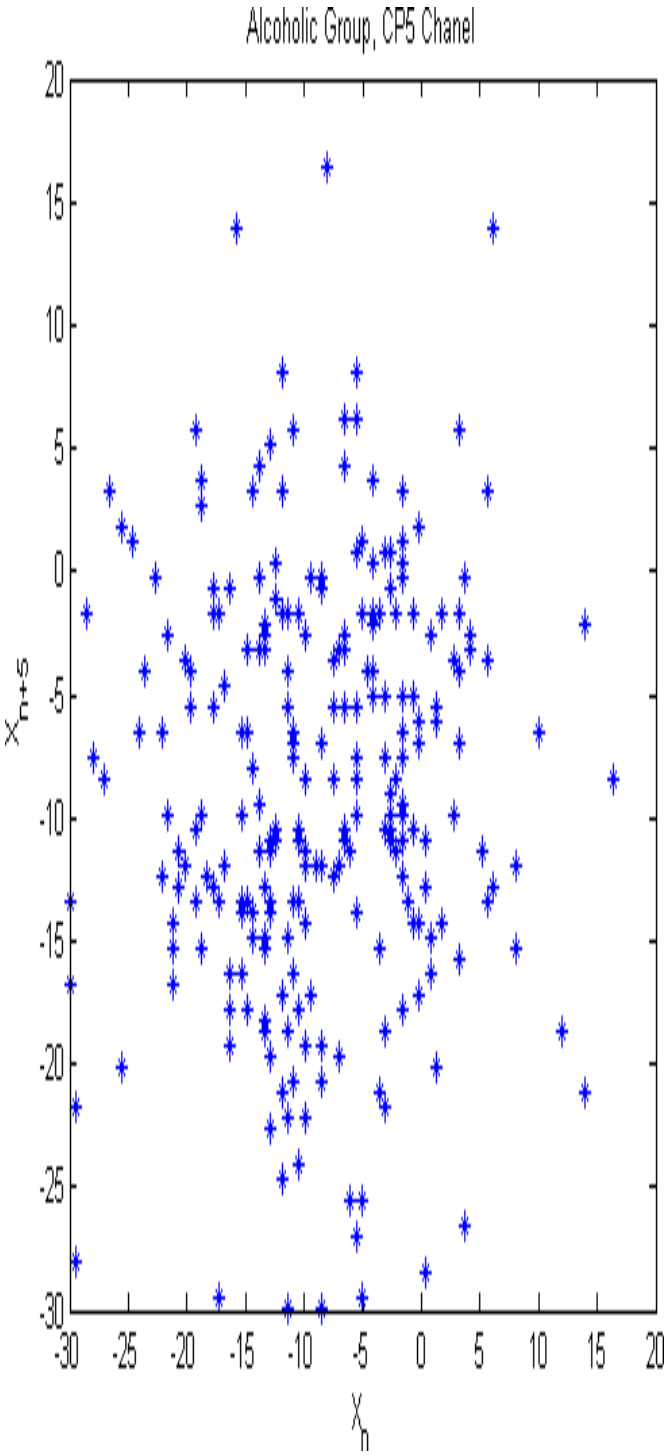
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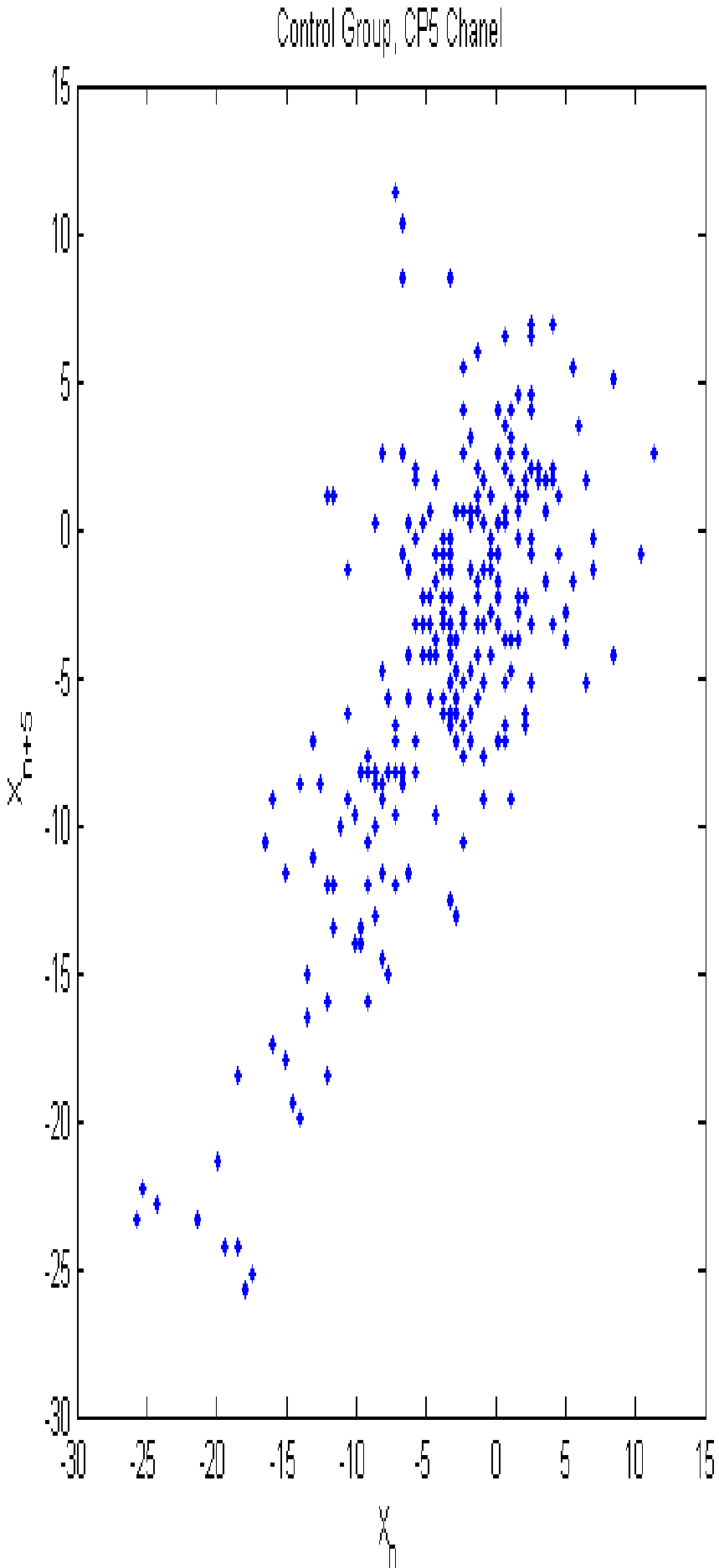
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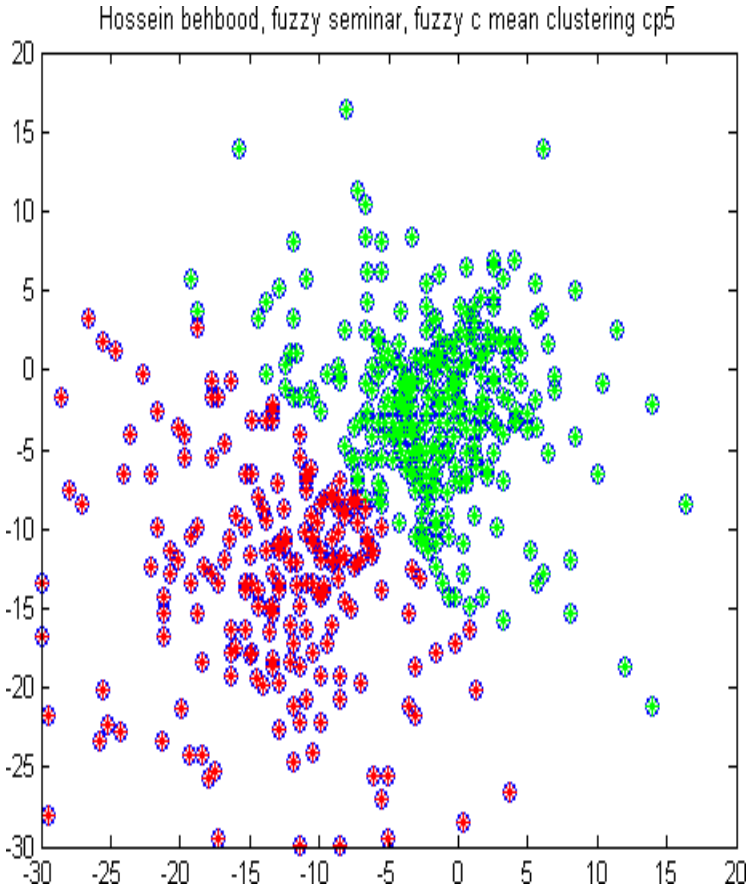
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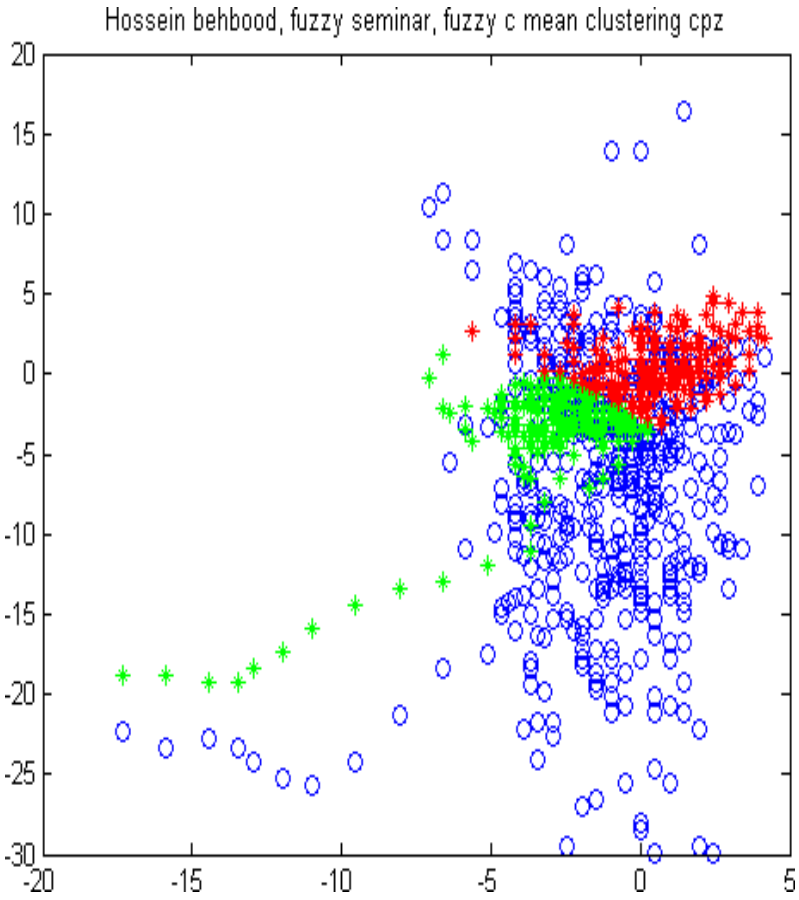
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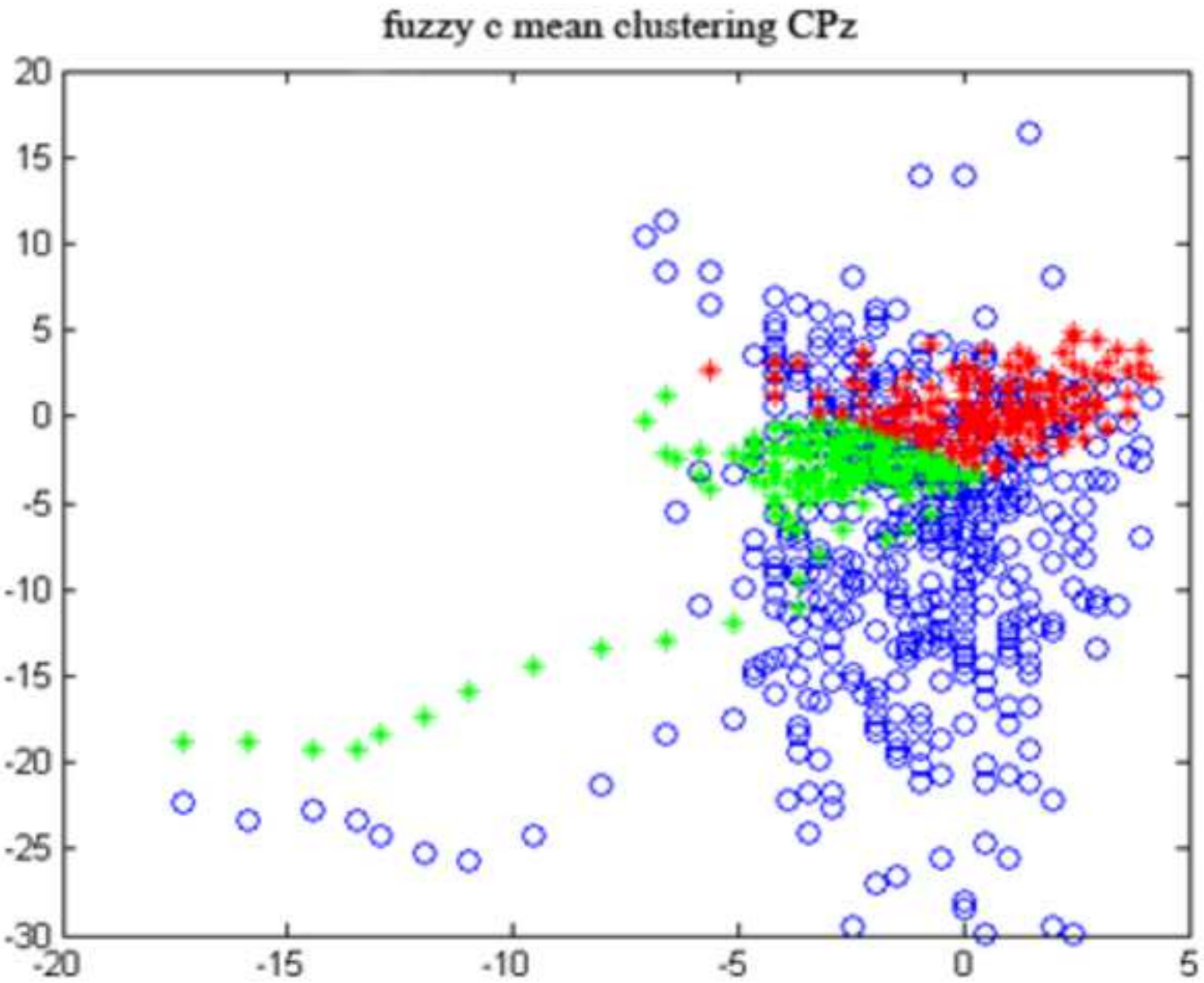

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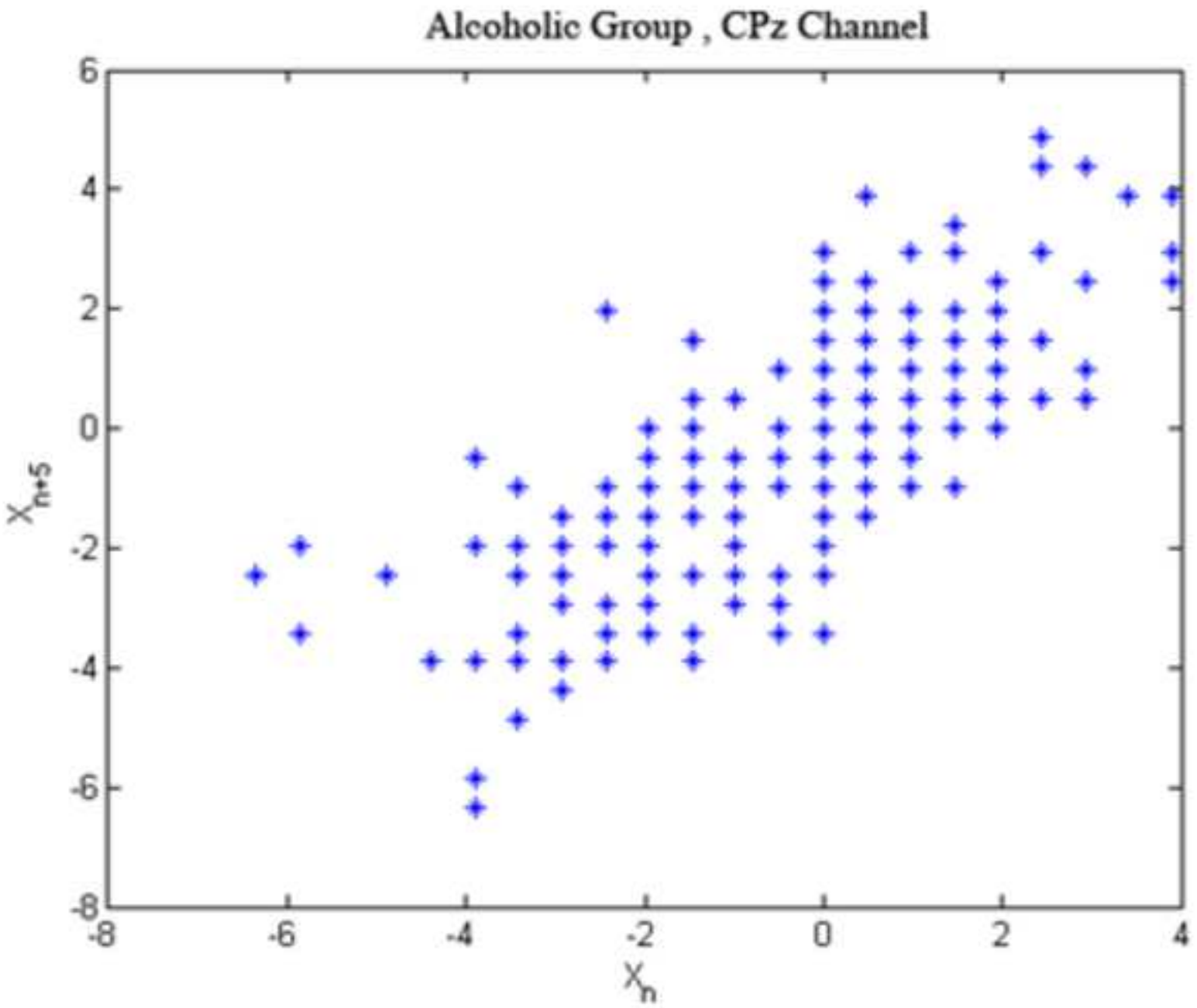

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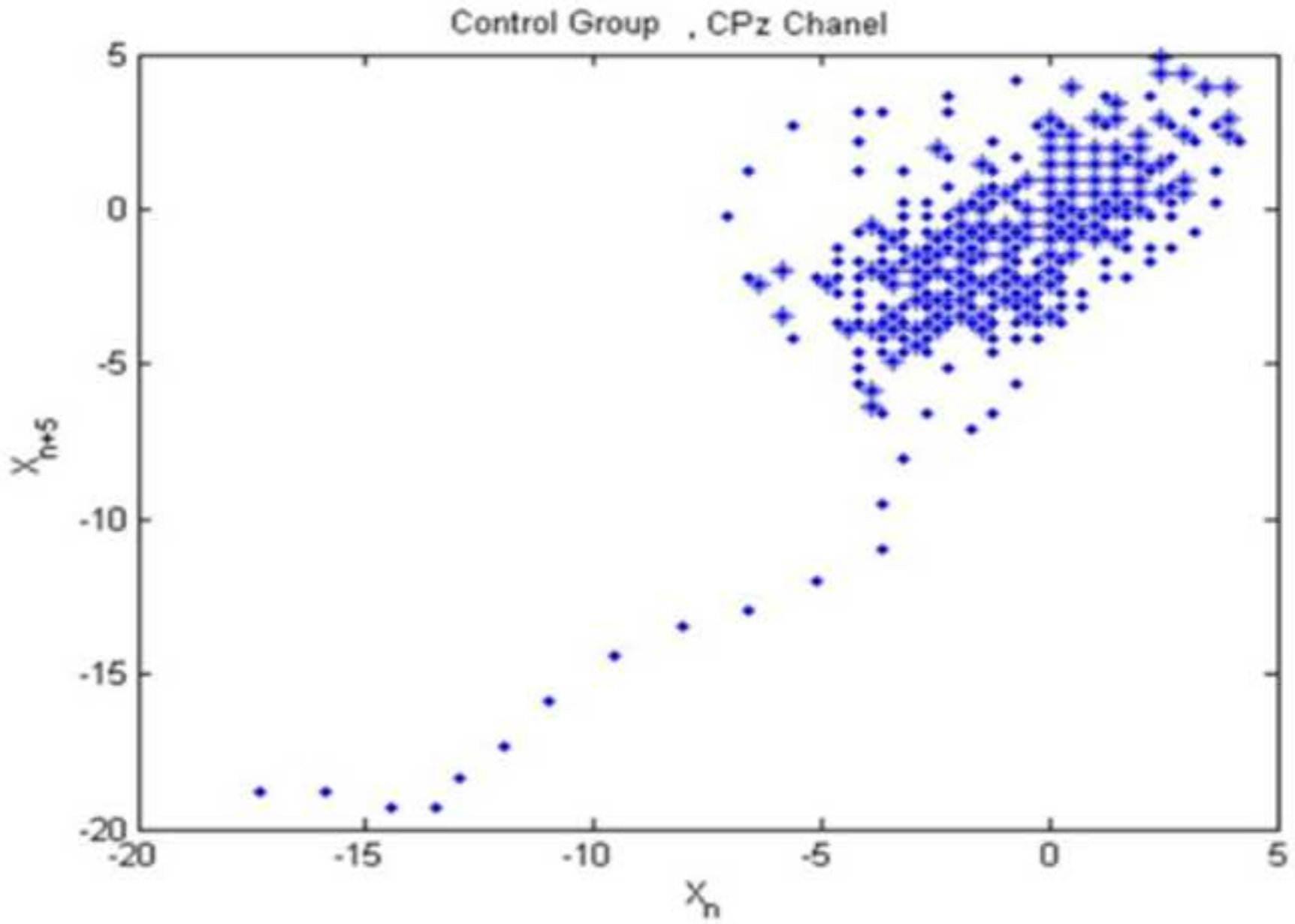

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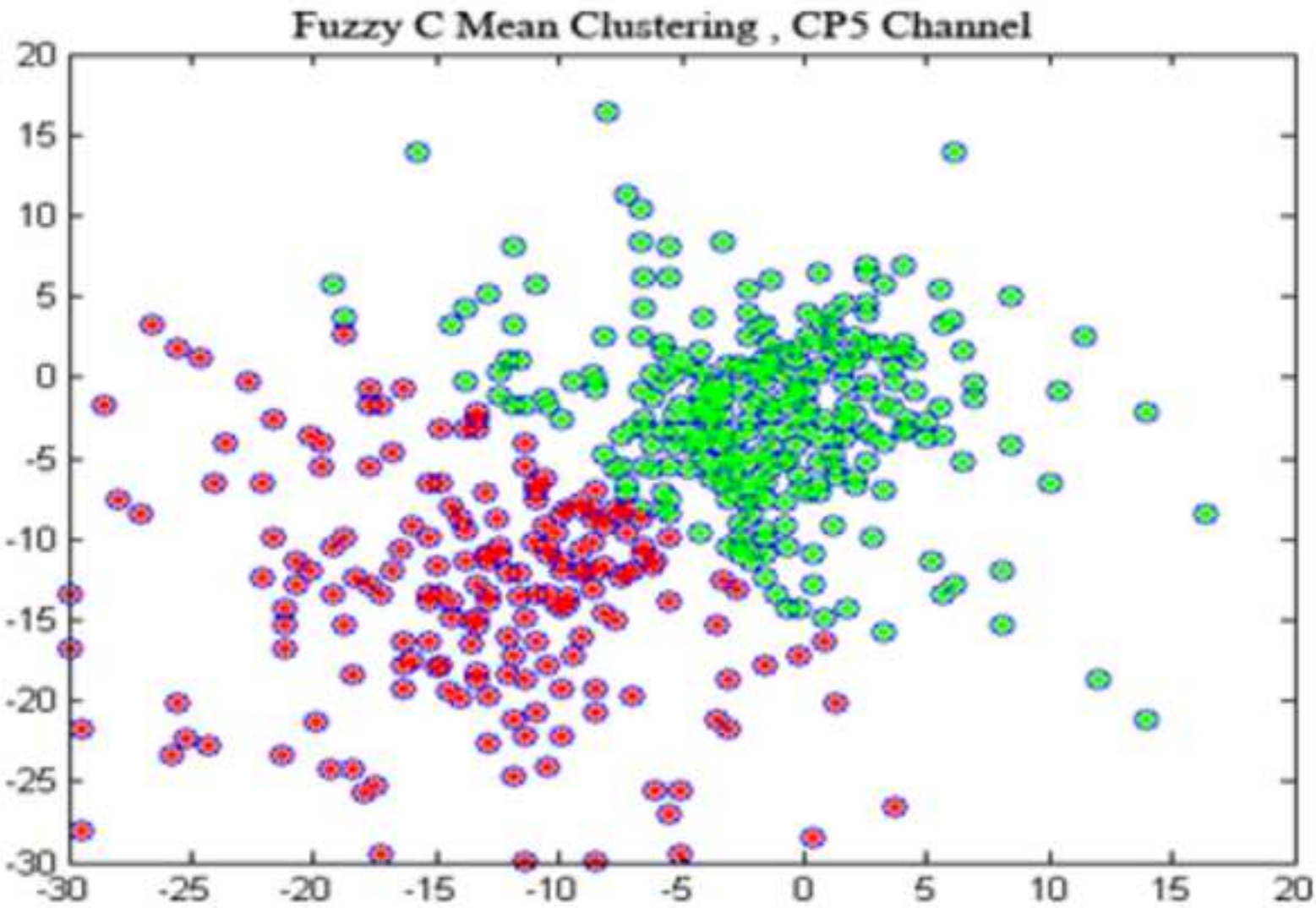

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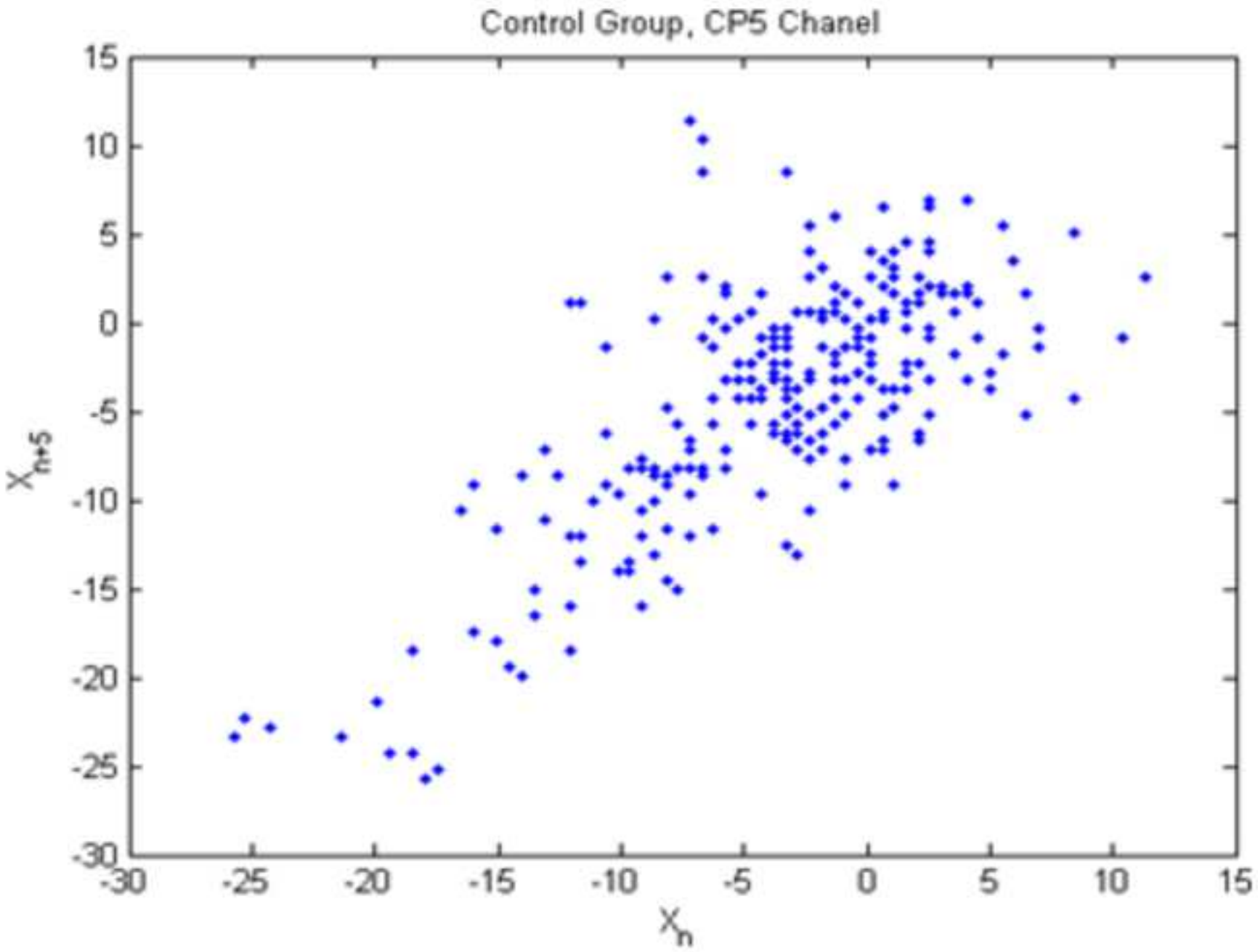

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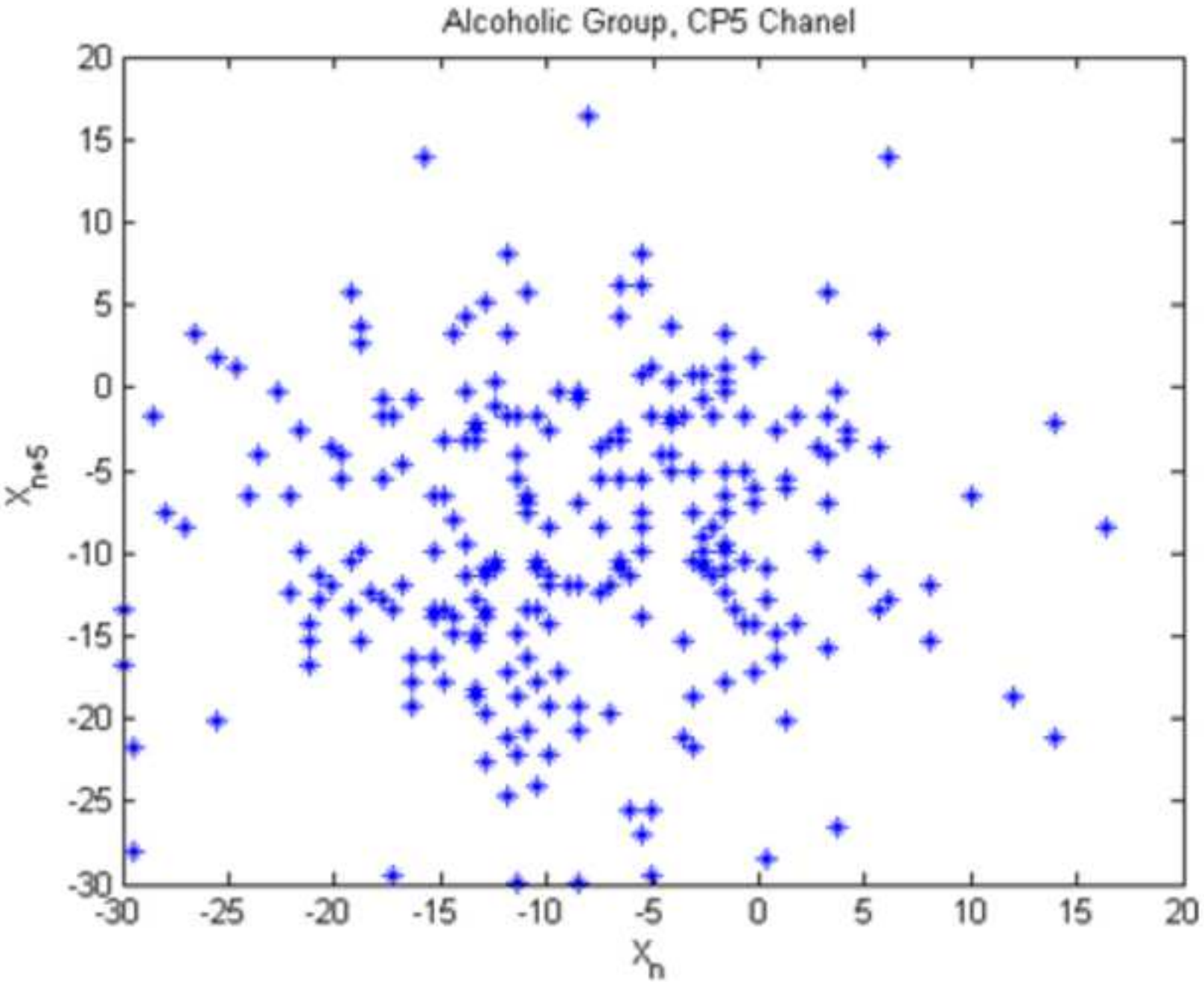

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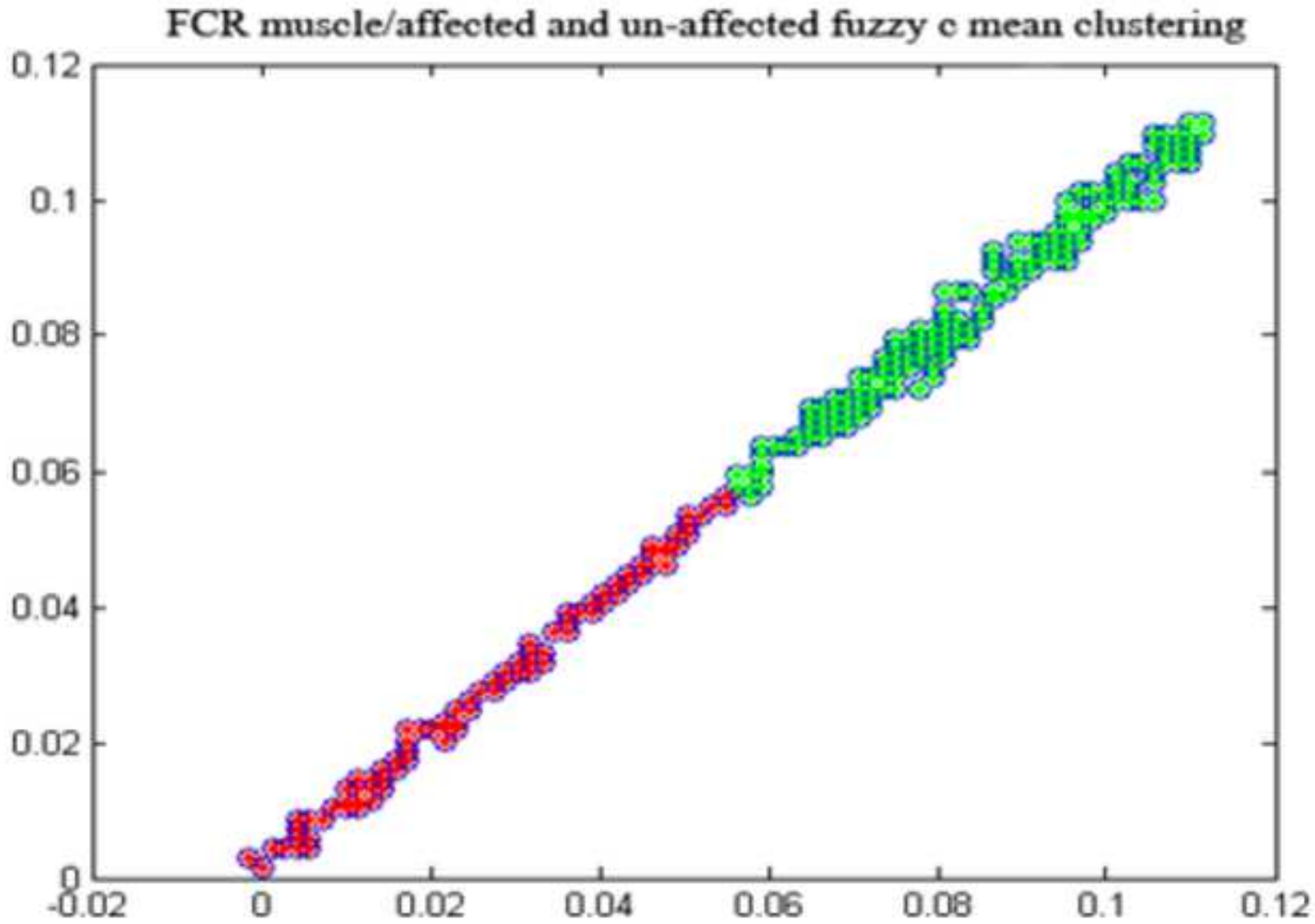

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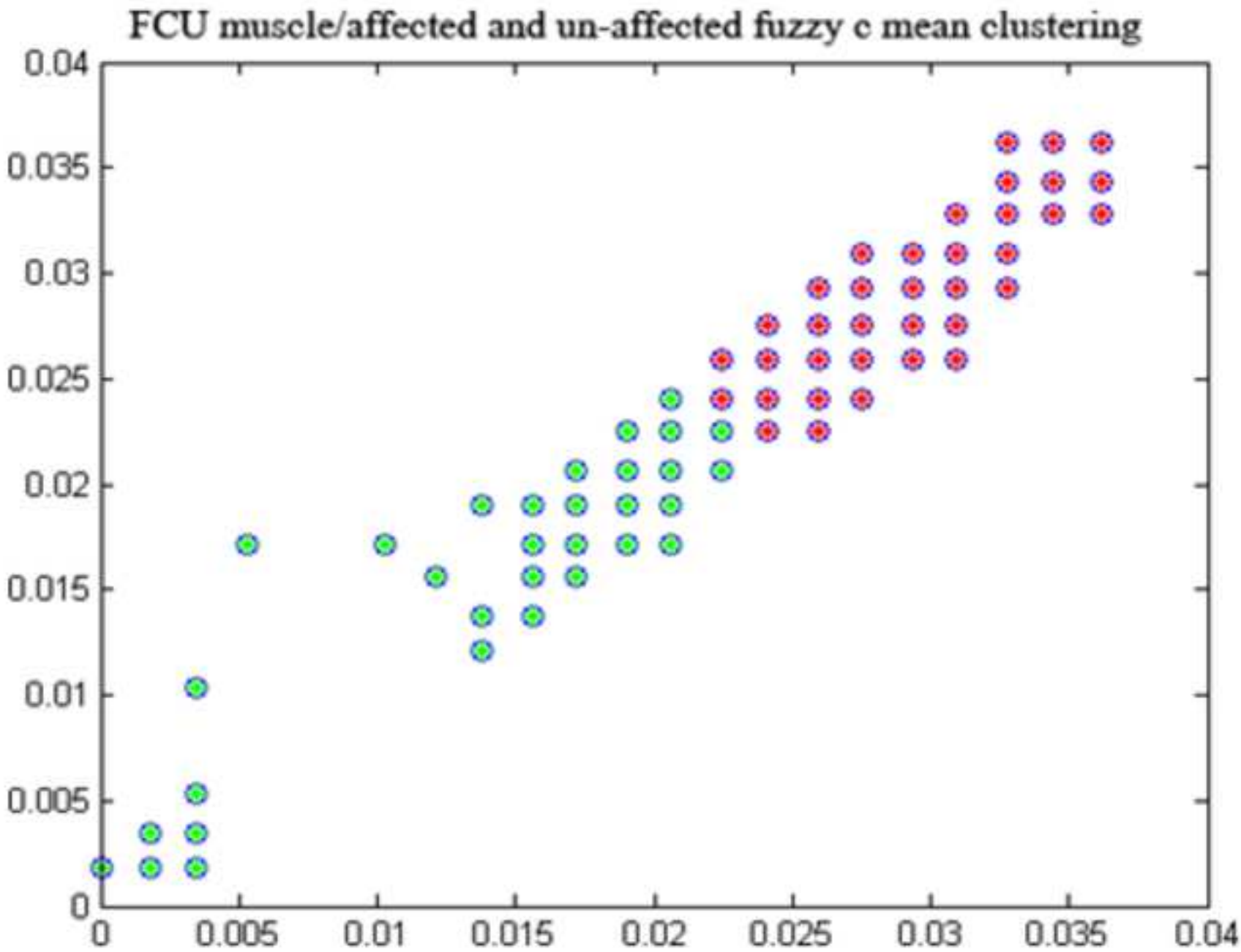

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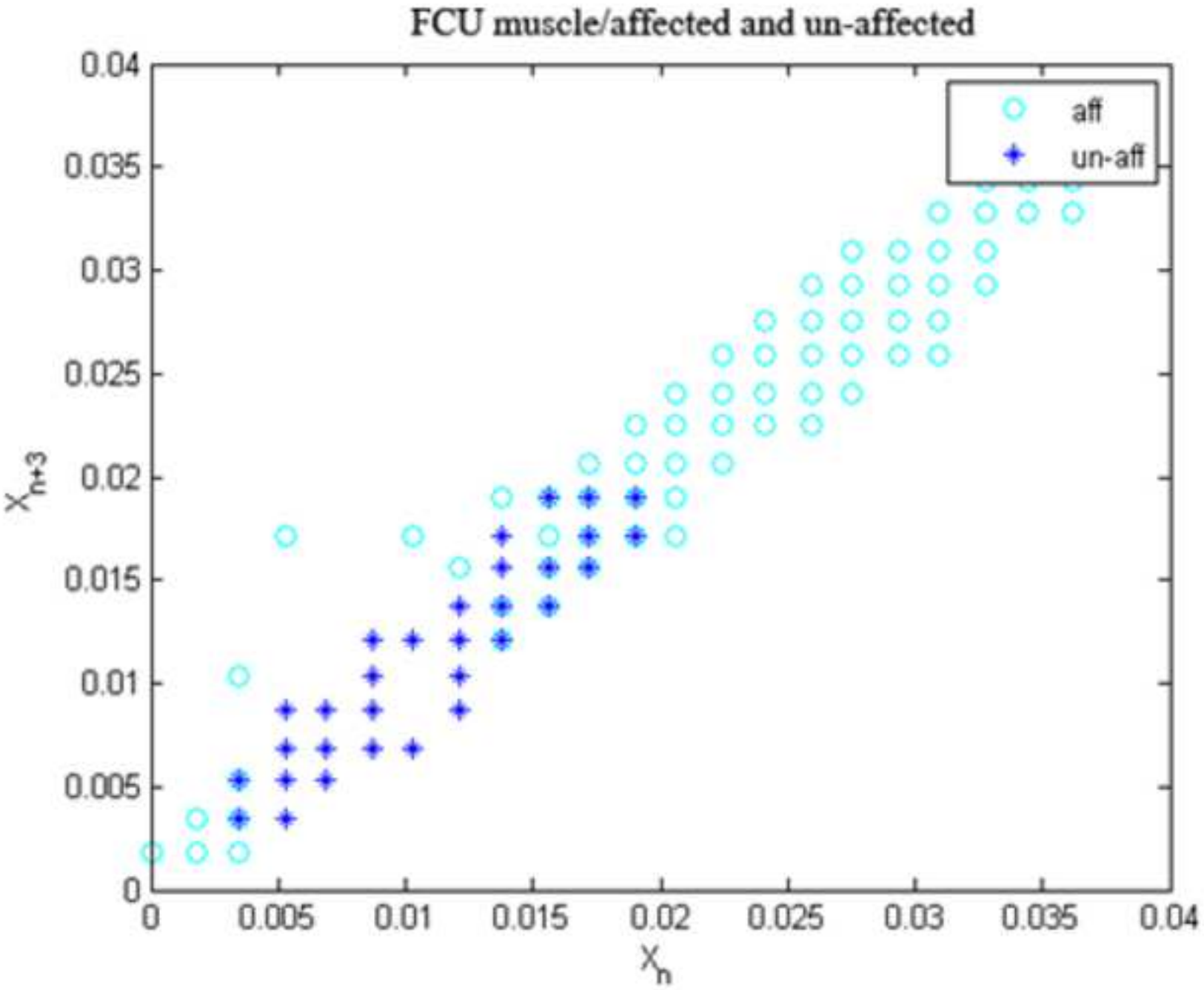

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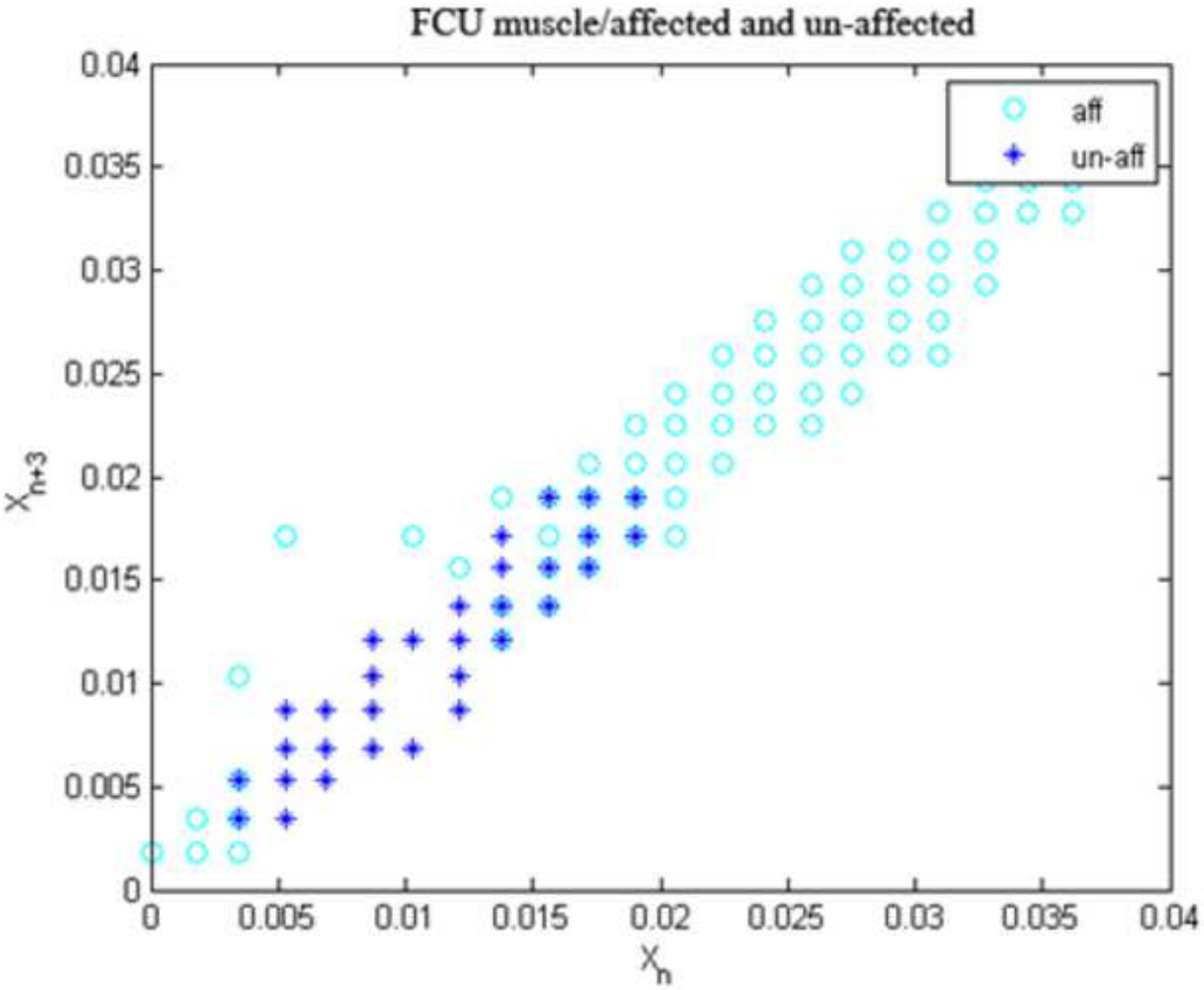

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