Canonical correlation of emg dystonic writers cramp - A study with micro electrode recordings for computational simulation and statistical models

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Abstract

In recent years, the advances in data collection and statistical analysis promotes canonical correlation analysis which is designated as C.C.A for multidimensionality and for multi-dimensional scaling purposes' offered for more advanced clinical research for effective medical diagnosis and also for outstanding results in medical prognostics. The C.C.A is the most important technique for dual-set data dimensionality reduction such that the correlation between the pairwise variables in the common subspace is equally or reciprocally or maximally increased. Over the 100 years of developments, a number of indeed a numerous myriad of C.C.A models and modalities, and computational simulations and statistical models with canonical correlation methods have got and ought to been suggested in accordance with as well as with artificial intelligence dissimilar machine learning mechanisms such as supervised (classification for instance random tree classification) learning and unsupervised learning (for instance principal components and various clustering algorithms like common and hard and soft and hierarchical clustering k-means and k-medoids)) techniques. Yet, the subject, i.e., field of research requires an intuitive study, analysis for the state-of-art developments.

Keywords: Canonical correlation analysis C C A, Multidimensional scaling, Multidimensionality

Introduction

In recent years, the advances in data collection and statistical analysis promotes canonical correlation analysis which is designated as C.C.A for multidimensionality and for multi-dimensional scaling purposes' offered for more advanced clinical research for effective medical diagnosis and also for outstanding results in medical prognostics. The C.C.A is the most important technique for dual-set data dimensionality reduction such that the correlation between the pairwise variables in the common subspace is equally or reciprocally or maximally increased. Over the 100 years of developments, a number of indeed a numerous myriad of C.C.A models and modalities, and computational simulations and statistical models with canonical correlation methods have got and ought to been suggested in accordance with as well as with artificial intelligence dissimilar machine learning mechanisms such as supervised (classification for instance random tree classification) learning and unsupervised learning (for instance principal components and various clustering algorithms like common and hard and soft and hierarchical clustering k-means and k-medoids)) techniques. Yet, the subject, i.e., field of research requires an intuitive study, analysis for the state-of-art developments.

Hence, this study aims and focuses to deliver and offer a regimented efficient and well-ordered outline for the C.C.A. plus its expansions and extensions for the future research. Exclusively, and in particular, we initially examine the C.C.A. theory as of the perception of both model-type prototype formation, i.e., the development structurally and model-type optimization. The connection amongst two standard resolution-solution methods, that is Singular Value Decomposition (SVD) and/or Eigen Value Decomposition (EVD), and Singular Value Decomposition (SVD) only, are examined. We then, demonstrate a categorization/taxonomy of existing developments and then categorize them into several conglomerates (i.e., clusters or groups), multi-view C.C..A, probabilistic C.C.A., and deep C.C.A., kernel C.C..A, discriminant C.C.A., sparse-C.C.A and then followed by the region or locality of vicinity protecting C.C.A. For every cluster, we determine, and we establish two or three characteristic or demonstrative exact mathematical and simulation-models, detecting their strengths and limitations. Then, we recapitulate the characteristic applications as well as numerical findings of these clusters in real time and real-world practices, accumulating or acquiring the kinds of datasets plus open sources for the application and execution. Finally, we offer several in fact a number of encouraging potential research paths which can enhance the existing state-of-art techniques.

Survey

With the swift expansion of data acquisition and data storage technique, a large volume of multi-view data in conjunction with high or very expensive dimensions are developing comfortable and straightforward to gain access to data. However, the three factors such as availability affordability and accessibility are very imperative in this regard.[1] Discovering the correlation as of multi variate data offers a very valuable in/put (I/p) for several in deed and in fact numerous data analysis problems, such as, innocuous micro electrode multi-site real-time / multi-channel-emotion-analysis,[2] signal-modeling and image-modalities multi-modal image-searching and image-acquisitions/gatherings and then extractions from images and to extrapolate for the desired/preferred or anticipated-information observing/or investigating for,[3-4] multi-view self-independent/autonomous driving[5] and multi-scale remote-monitoring.[6] To explore the multi-modal-correlation, one must meet the following-issues: the desired-intrinsic-features are continuously embedded into complex high-dimensional-spaces, which limits the statistical-analyzing-performance, and also dissimilar spaces spanned by dissimilar view samples continuously hold distinct dimensions, which makes the unswerving connection computation unreasonable,.[5-15] As a powerful tool for multi-modal/feature-fusion, canonical-correlation-analysis (C.C.A.) has gained extensive thoughts and though processes.[16-21]

Canonical correlation analysis – Multidimensionality for Multidimensionality Scaling

Computing with the statistical techniques

A canonical correlation analysis between the right hand writing signal (RHWS) and left hand writing signals (LHWS) for each patient was carried - out, giving the following sq canonical correlations Table AB (see below).

Table AB: Sq canonical correlations

Patient	λ1	λ2	λ3	λ4	λ5	Discordant
A1	0.6527	0.3015	0.0006	0.0003	0.0000	D
A2	0.1566	0.0023	0.0004	0.0001	0.0000	
A3	0.0021	0.0015	0.0002	0.0002	0.0000	
A4	0.1734	0.0018	0.0004	0.0000	0.0000	
A5	0.0383	0.0018	0.0015	0.0001	0.0000	
A6	0.0509	0.0033	0.0011	0.0004	0.0001	
A7	0.0022	0.0014	0.0009	0.0008	0.0000	D
A8	0.0799	0.0018	0.0004	0.0002	0.0000	
A9	0.2615	0.0707	0.0030	0.0002	0.0000	
A10	0.0502	0.0069	0.0009	0.0004	0.0001	
A11	0.0034	0.0021	0.0006	0.0002	0.0000	D
A12	0.0013	0.0006	0.0002	0.0002	0.0000	D

D = Discordant group; λ_1 λ_2 λ_3 λ_4 λ_5 are squared canonical correlations

The canonical variates defined for 2 sets of variates observed on the same "individuals" are pairs of linear combinations of the two sets, which are successively, and maximally in succession, correlated with each other, but uncorrelated with other such sets. In the present case one can construct a combination of right hand signals and a combination of the left hand signals, which have a maximum possible correlation. If the correlation is high enough, it would mean that the two signal sets are somehow interrelated – possibly the same causal mechanism being responsible for the signal patterns in the right and left hand signals. Otherwise, the two sets of signals appear to be independent of each other on the whole.

In the present case, the squared canonical correlation is at least 0.15 only in patients A1 (0.65), A2 (0.16), A4 (0.17), and A9 (0.26), all other first canonical correlations themselves being small (<0.10). That is, in these 4 cases there is some possible similarity in the two sets of signals. Further, A1 has a second canonical correlation relatively high (0.30). Hence, in the case of patient A1 there is one more pair of combinations which are uncorrelated with the first pair suggesting possibility of two mechanisms which together give rise to the overall signals.

Individual Patients Correlational Data Computations and Analysis

Correlation between signals from different muscles in the same hand

The correlations, for each patient, between the signals when writing with the right hand and when writing with the left hand are given in the Tables of appendix-III. Though mostly the correlations are negligible, some correlations are quite significant and markedly high. These are presented below as a Table of significant correlations (i.e., correlations which are greater than (>) 0.50 in absolute value.

It is found that often, the same muscle pairs will have significant correlation with same sign, in both the 'hand-signals' (i.e., RHWS and LHWS).

The muscle pairs have had significant correlation with same sign, in both LHWS and in RHWS

Table AE: Matrix representation

	ECR	ECU	FCR	FCU	5th-Muscle
ECR		+	+	-Ve	+
ECU	*		+	-Ve	-Ve
FCR	+	+		-Ve	-Ve
FCU	-Ve	-Ve	-Ve	*	-Ve
5-th Muscle	+	-Ve	-Ve	-Ve	*

In other words, if at all significantly correlated, in the above matrix representation, the ECR muscle correlates positively with muscle FCR and 5th muscle. And also muscle ECR correlates negatively with muscle FCU, and muscle FCR correlates negatively with muscles FCU and 5th. Muscle FCU correlates negatively with 5th muscle apart from muscles ECR, ECU and FCR. This scenario can be seen in the matrix representation Table AE.

Similarity investigations based on significance of Means, (t-Values) and Variances (F-ratio)

As already noted, from the 12 patients analysis of the means (μ or x) and standard deviations (σ) and significance of their differences between the 5 muscle pairs (of LHWS and RHWS), for each of the 12 patients, we get the following table of similarity/ dissimilarity,

Tables AF and AG (xt and xf see below) are indicator matrices for the differences in mean and for the differences (as measured by the ratio of variances) in variability of amplitudes.

Table AF: Patterns of significance of t_values xt =

0	0	0	0	0
-1	-1	1	-1	-1
1	1	-1	1	1
0	0	0	0	0
0	1	0	0	0
-1	1	1	-1	-1
0	0	0	0	0
1	0	0	0	0
0	-1	0	-1	0
-1	0	1	-1	-1
-1	0	1	-1	-1
1	0	1	-1	0

Table AG: Patterns of significance of f_values xf =

0	1	1	1	1
1	0	0	1	1
-1	-1	-1	-1	-1
0	0	0	0	0
0	1	0	0	0
1	1	1	1	1
1	1	0	0	1
1	0	0	0	0
0	-1	1	0	0
0	1	0	0	0
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1

For example, xt (2,1) = -1, indicating that, for patient 2, in the first pair of muscles (ECR) the average value of right hand muscle is significantly less than the average value of the left hand muscle, xt(i,j)=0 indicates that the difference is not significant, as for instance, in xt (1,1) = 0.

Similarly for the table xf, 1 indicates right variance > left variance, while -1 indicates right variance < left variance and 0 indicates that the two variances are 'effectively-the-same', as indicated by the F-ratio.

From these tables, the tables of (squared) Euclidean distances (SED) between the 12 patients are computed and presented as the Tables AH and AI (see dxt and dxf given below) respectively.

Conclusions

For all 12 patients, the first row's indicate the distances of patients in the increasing order, based on their f-ratios, where as second rows indicates the patients identities.

On the basis of variance dominance pattern, patients {A4, A5} and {A6, A10, A11, A12} form two perfect clusters.

However, there is no clear differentiating feature between discordant {A1, A7, A11, A12} and concordant group.

In so far as these measures are relevant, one should find that clinically also, the patients who differ most on this basis should also show sufficiently different clinical pictures. If this validation is not coming forth by clinical examination, one has to conclude that these parameters, by themselves, are not helpful in the differential diagnosis of the patients, in recognizing the affected muscles, etc.

Source of Funding

None.

Conflict of Interest

None

References

1. C. Xu, D. Tao, and C. Xu, "A survey on multi-view learning," 2013, arXiv:1304.5634.
2. S. Eleftheriadis, O. Rudovic, and M. Pantic, "Discriminative shared gaussian processes for multiview and view-invariant facial expression recognition," *IEEE Trans. Image Process*., vol. 24,(1). 189–204, Jan. 2015.
3. J. Yu, X. Yang, F. Gao, and D. Tao, "Deep multimodal distance metric learning using click constraints for image ranking," *IEEE Trans. Cybern.*, Vol. 47,(12) 4014-24, Dec. 2017.
4. J. Yu, Y. Rui, and D. Tao, "Click prediction for web image rerank- ing using multimodal sparse coding," *IEEE Trans. Image Process.*, Vol. 23,(5), pp. 2019–32, May 2014.
5. Oppenheim H: Über eine eigenartige Krampfkrankheit des kindlichen und jugendlichen Alters (Dysbasia lordotica progressiva, Dystonia musculorum deformans). *Neurol Centralbl* 1911; 30: 1090–1107.
6. Ziehen GT: Ein Fall von tonischer Torsionsneurose. Demonstrationen im Psychiatrischen Verein zu Berlin. *Neurol Zentralbl* 1911; 30:109–10
7. E.Altschuler; Ramazzini and writer's cramp,*Lancet*, Volume 365,(9463),938
8. Gowers WR.A manual of diseases of the nervous system.*Churchill London* 1888. Vol-2 656-74
9. Collier J, Adie WJ.IN: A textbook of practice of medicine. Ed: Price F W. Trowde, *Hodder and Stoughton, London*,1922:1462-66
10. Marsden 1976, Sheehy MP, Marsden CD.Writer's cramp–a focal dystonia. *Brain* 1982;105:461–80
11. Fahn S, Marsden CD, Calne DB. Classification and investigation of dystonia. In: Marsden CD, Fahn S, eds. Movement disorders 2. London: Butterworths, 1987:332-58.
12. Bressman SB. Dystonia genotypes, phenotypes, and classification. *Adv Neurol* 2004;94:101-7,

13. Fahn S, Bressman SB, Marsden CD. Classification of dystonia. *Adv Neurol* 1998;78:1-10.
14. de Carvalho Aguiar PM, Ozelius LJ. Classification and genetics of dystonia. *Lancet Neurol* 2002;1:316-25.
15. Nemeth AH. The genetics of primary dystonias and related disorders. *Brain* 2002;125:695-721.3-7
16. Nutt JG, Muenter MD, Aronson A, et al. Epidemiology of focal and generalized dystonias in Rochester, *Minnesota. Mov Dis* 1988; 3: 188-94. Links
17. The ESDE (Epidemiological Study of Dystonia in Europe) Collaborative Group. A prevalence study of primary dystonia in eight European countries. *J Neurol* 2000; 247: 787-92. Links
18. Castelon-Konikiewitz E, Trender-Gerhard I, Kamm C, et al. Service-based survey of dystonia in Munich. *Neuroepidemiology* 2002; 21: 202-6. Links
19. Muller J, Kiechl S, Wenning GK, et al. The prevalence of primary dystonia in the general community. *Neurol* 2003; 61:(1) 1294-1296. Links.

How to cite: Raju.V R et al. Canonical correlation of emg dystonic writers cramp - A study with micro electrode recordings for computational simulation and statistical models *IP Int J Aesthet Health Rejuvenation* 2021;4(4):.