A Visualization System to subdiveide Dementia Diagnosis Stages

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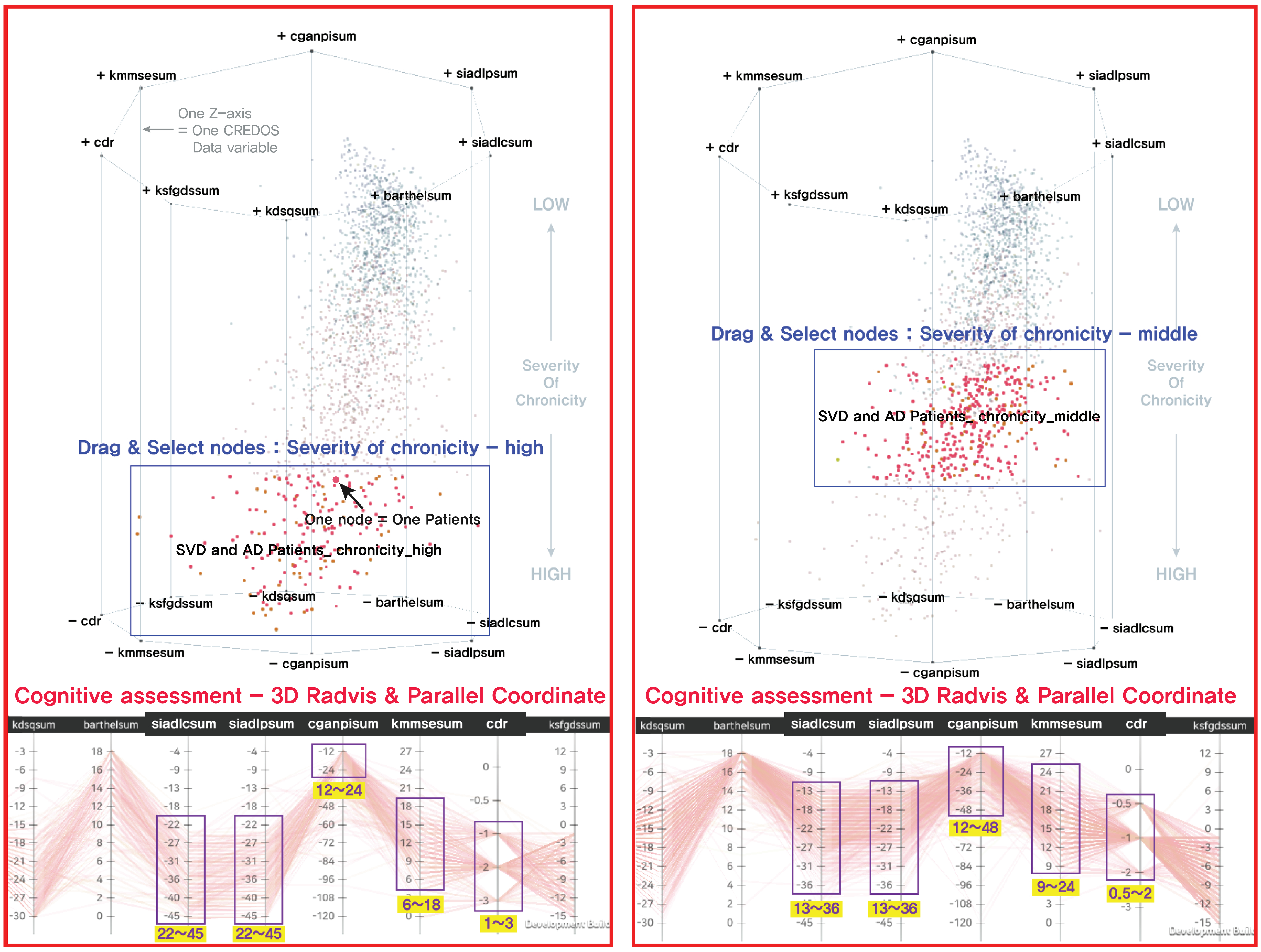

Figure 1. A Visualization analysis system to subdivide dementia diagnosis stages. (Left) Filtered nodes of high chronic grade among nodes of AD and SVD (Alzheimer's Disease and Subcortical Vascular Dementia), (Right) Filtered nodes of moderate chronic grade among nodes of AD and SVD.

Abstract

This research suggests a visualization system facilitating a more detailed analysis through subdividing characteristics within patient groups. We first refined the cohort data of examination records of dementia patients while consulting with medical professionals involved in dementia diagnosis. We then adopted a visualization technique combining 3D Radvis and Parallel Coordinate for multidimensional data analysis. As a result, variables in cognitive assessments were identified to be more important indicators than physical examinations. If the chronic grades vary within a group of a specific disease stage, it appeared to be effective to consider the total score of current functioning and latent ability in S-IADL, CGA-NPI, K-MMSE and CDR grade.

Objectives

This paper thus identified data in various perspectives with a multi-dimensional visualization tool, and studied the differences between scores on each diagnosis stage by comparing the diagnosis results. Based upon the refined CREDOS data, we visualized the distribution of dementia diagnosis assessment results through two techniques: 3D Radvis with Scatter plots on a three dimensional and parallel coordinate which showed each result as a line graph. Next, through a case study, key variables were extracted to subdivide and analyze the patients. We also designed an analysis method to subdivide a group with a specific disease stage when the chronic grade within the group varies.

Data Processing

We have conducted a cohort analysis based upon the diagnosis data of dementia patients in CREDOS(Clinical Research Center for Dementia of South Korea) collected in 30 hospitals nationwide from 2005 to 2013. This includes 21,000 diagnosis records of 14,000 patients, some of which are follow-up reports on diagnosis. Table 1 illustrating the types of examinations included in our data.

Data type	Data explanation
Patient information	Government ID, Cohort ID, Personal information (gender, age, level of education), Patient History
Caregiver information	Caregiver personal information (gender, age, relation)
Psychological testing information	KDSQ(Korean Dementia Screening Questionnaire), CGA-NPI(Caregiver-Administered Neuropsychiatric Inventory), Barthel-IADL(Barthel Index of Activities of Daily Living), S-IADL(Seoul-Instrumental Activities of Daily Living), GDS(Global Deterioration Scale), CDR(Clinical Dementia Rating Scale), K-MMSE(Korean Vision of Mini-Mental State Exam), SNSB(Seoul Neuropsychological Screening Battery), KSF-GDS(Korean Seoul Form of Geriatric Depression Scale)
Neurologic examination	MRI data (Brain volume), Neurological examination from dementia
Expire information	Criteria: ICD-10 (Cause of Expire) Expired date (Year, Month, Day)

Table 1. Data type included in the CREDOS Cohort.

Visualization Methods

We adopted 3D Radvis [1] and Parallel Coordinate to analyze the diagnosis record data in various aspects. Visualization through 3D Radvis enables this subdivision by considering the difference of heights, since the location information of each node ultimately illustrates the medical status of a patient. By interpreting the assessment results presented in 3D Radvis as line graphs in parallel coordinates, we aimed to analyze diagnosis patterns in a more detailed way along with 3D Radvis. We also focused on the changes in line graphs according to chronic grades in order to choose types of assessments contributing to subdivision of diagnosis stages.

Implementation

Figure 1 suggests the distribution of nodes after we filtered them according to severity of chronicity. Nodes with high chronic grades are presented in the left polygon while the right polygon illustrates nodes with moderate chronic grades. We proceeded to compare the parallel coordinates between the left and right polygon in order to discover a variable to subdivide patients according to their chronic grades. Whereas a total score of KDSQ, Barthel-IADL and GDSSF-K showed analogous line distributions regardless of its chronic grade, groups of distinct chronic grades showed a significant difference in Current Functioning and Latent Ability sections in S-IADL, a total score in CGA-NPI, K-MMSE and CDR grade.

In patient group with high chronic grades, the total score in Current Functioning and Latent Ability sections in S-IADL was 22 to 45, 12 to 24 on CGA-NPI, 6 to 18 on K-MMSE and 1 to 3 on CDR grade. Patient group with moderate chronic grades however showed a total score of 13 to 36 in Current Functioning and Latent Ability sections in S-IADL, 12 to 48 on CGA-NPI, 9 to 24 on K-MMSE and 0.5 to 2 in CDR. We thus discovered that the total score of Current Functioning and Latent Ability sections in S-IADL was 22 to 45, 12 to 24 on CGA-NPI, 6 to 18 on K-MMSE and 1 to 3 on CDR grade. Patient group with moderate chronic grades however showed a total score of 13 to 36 in Current Functioning and Latent Ability sections in S-IADL, 12 to 48 on CGA-NPI, 9 to 24 on K-MMSE and 0.5 to 2 in CDR. We thus discovered that the total score of Current Functioning and Latent Ability sections in S-IADL, CGA-NPI, K-MMSE and CDR grade were meaningful indicators to subdivide the diagnosis stages, which can be beneficial for medical professionals to diagnosis patients with Alzheimer's disease and Subcortical Vascular Dementia in various ways.

Conclusion

This tool, based on the comparison between the results of cognitive and neurological assessments by each diagnosis stage, can contribute to healthcare informatics since it is expected to facilitate a decision-making process for medical professionals. We also created an additional dimension in our visualization, in order to present multi-dimensional variables in medical data. We further plan to conduct a visualization evaluation on clinicians specializing in dementia study and diagnosis, and to investigate whether 3D Radvis is actually a useful tool for medical data analysis and decision making on diagnosis.

References

[1] A. Ibrahim, S. Rahnamayan, M.V. Martin, K. Deb. 2016. 3D-RadVis: Visualization of Pareto front in many-objective optimization. In Proceeding of the Congress on Evolutionary Computation (CEC 2016). IEEE, Vancouver, Canada, 736-745.