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Visualizing Geographical Contexts in Social Networks

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ABSTRACT

We propose a method for geographically enhanced representation of social networks and implement a Web-based 3D visualization of geographical contexts in social networks. A renovated social network graph is illustrated by using two key components: (i) GWCMs (geographically weighted centrality measures) that reflect the differences in interaction intensity and spatial proximity among nodes and (ii) MSNG (map-integrated social network graph) that incorporates the GWCMs and the geographically referenced arrangement of nodes on a choroplethic map. For the integrated 3D visualization of the renovated social network graph, we employ X3D (Extensible 3D), a standard 3D authoring tool for the Web. An experimental case study of regional R&D collaboration provides a visual clue to geographical contexts in social networks including how the social centralization relates to spatial centralization.

Keywords : Social Network, 3D Geovisualization, Web-based GIS

요 약

이 논문에서는 지리적 표현이 보강된 사회네트워크 모형을 제시하고, 이 모형을 통해 사회네트워크의 지리적 맥락을 시각화하는 3D 웹서비스를 구현한다. 이 연구에서 제안하는 사회네트워크 그래프 개선의 핵심요소는 (i) 네트워크 노드들의 상호작용 강도 및 공간적 인접성이 반영된 '지리적 가중치가 부여된 중심화 지수' 그리고 (ii) 이러한 중심화 지수를 3차원 심볼을 이용하여 표현함과 동시에 네트워크 노드들을 단계구분도와 중첩하여 시각화하는 '지도와 결합된 사회네트워크 그래프'이다. 개선된 사회네트워크 그래프는 X3D (Extensible 3D)를 이용하여 구현하였으며, 시도간 R&D 협력의 사례분석을 통해 그 적용가능성이 확인되었다. 이 논문에서 제시하는 방법론은 사

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회네트워크에 내재하는 공간적 집중화의 경향 등 기존의 네트워크 분석에서 간과되었던 사회네트워크의 지리적 맥락에 대한 시각적 단서를 제공한다.

주요어 : 사회네트워크, 3차원 지리적시각화, 웹기반 지리정보시스템

1. Introduction

Social network is a social structure in which a set of nodes are connected by a set of ties (Watts, 1999; Scott, 2000). It helps interpreting how the nodes such as individuals, organizations, corporations, regions, or nations interact in a variety of relationships. One of the important indices for the social network analysis based on a graph theory (Erdös and Rényi, 1960) is centrality measures that explain the relationship patterns among interacting nodes by highlighting the differences between important and non-important nodes (Wasserman and Faust, 1994). For example, degree centrality denotes how many ties are connected to a node, and closeness centrality indicates how close a node is to the others.

From a perspective of geographical information, it is notable that most research in social networks assumes purely relational space, without much consideration of geographic space (Gorman and Kulkarni, 2004; Metcalf and Paich, 2005). Some of the previous works suggest several methods of weighted network graph or centrality measure to discover the complex structure of social networks (e.g., Newman, 2001b; Liben-Nowell *et al.*, 2005; Cornwell, 2006; Kretschmer and Kretschmer, 2006; Thadakamalla *et al.*, 2006). However, they fail to include the effect of spatial factors that help understanding the complex structure of social networks. If the ties of nodes are analyzed by spatial interactions such as regional collaboration, a geographically weighted method of centrality measures and a geographically referenced arrangement of nodes would contribute to understanding a geographical context in social networks.

Regarding mentioned above, we can throw a question like "Does geographic accessibility affect centrality?". If the geographic accessibility (or spatial proximity) is influential, so-called distance decay is observed in social networks. Otherwise, we can assume that a central node with low geographic accessibility or a non-central node with high geographic accessibility has its own socioeconomic background of the centrality. Thus, the representation of social networks may need modifications for providing a visual clue to such geographical contexts in social networks.

In this paper, we present a method for geographically enhanced representation of social networks and implement a Web-based 3D visualization of geographical contexts in social networks. We develop GWCMs (geographically weighted centrality measures) for reflecting spatial factors in social networks. Degree and closeness centrality, the most commonly used measures for social network analysis are modified by the weight matrices based on interaction intensity and spatial proximity. Moreover, we show MSNG (map-integrated social network graph) as a reinforcement of existing social network graphs (Figure 1) that incorporates the GWCMs and the geographically referenced arrangement of nodes. A simultaneous representation of both elements in our renovated social network graph is combined with a map for more intuitive capturing of geographic distribution. It includes a choroplethic map for comparing the centrality measures of network with the socioeconomic variables of node. Since a geovisualization in a 3D space can facilitate the integration of necessary elements for geographically enhanced social network graph, we employ X3D (Extensible 3D) in representing a renovated social network graph on the Web.

2. Geographical Contexts in Social Networks

Although most research tends to examine social networks as a non-spatial phenomenon, the location, distance, and geography may be vital aspects of a variety of social networks (Gorman and Kulkarni, 2004). It is true that spatial factors in social networks have been taken into account, whether explicitly or implicitly. From a viewpoint of cost versus benefit, being connected benefits a node whereas maintaining relationship is costly; hence, social networks can be formed based on the comparison of cost and benefit (Johnson and Gilles, 2000). One of the cost measures is the distance matrix among nodes (Debreu, 1969; Newman, 2001a; Nybloma *et al.*, 2003; Liu *et al.*, 2005; Ravi *et al.*, 2005) using Euclidean distance, time distance, traffic distance, routing distance, mental distance, etc. The potential benefit can be a tangible or intangible outcome that depends on the goal

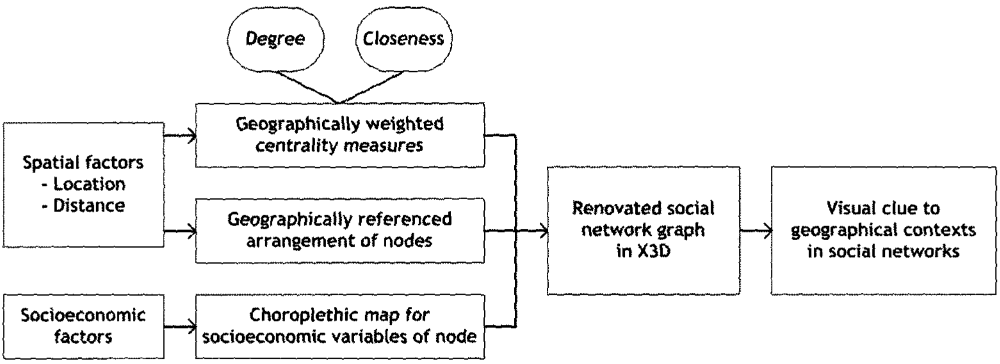


Figure 1. Renovated social network graph in X3D

of participating nodes in social networks.

In a visualization environment, a social network graph is a formalized representation of the social networks composed of nodes and ties. However, the locations of nodes in the graph do not have geographical meaning, because the arrangement of nodes has been considered a matter of artistic vision (Freeman, 2000). In order to deliver geographical meaning to a social network graph, Dibble and Feldman (2004) attempt to visualize the location of moving nodes, and Wong *et al.* (2006) draw a spatial random graph in a virtual space. However, centrality measures do not seem to be sufficiently integrated with network graph visualizations in a geographic aspect such as mapping. Since maps can stimulate visual thinking about geographical patterns, relationships, and trends (Kraak, 2004), a social network graph combined with maps can′ facilitate the understanding of geographical contexts in social networks.

3. Proposed Method

Our renovated social network graph consists of two components: (i) GWCMs that reflect the differences in interaction intensity and spatial proximity among nodes and (ii) MSNG that incorporates the GWCMs and the geographically referenced arrangement of nodes on a choroplethic map. These two components are accommodated in a 3D geovisualization on the Web.

3.1 Geographically Weighted Centrality Measures

Appropriate weighting scheme is crucial to centrality measures in social networks (Leenders, 2002). One of the appropriate weighting schemes for centrality measures is the interaction intensity matrix calculated by using the proportion of inter-node interactions such as trade, information exchange, and academic collaboration. Besides, in order to reflect spatial factors to the weighting scheme, a spatial proximity matrix needs to be incorporated into the centrality measures. The spatial proximity of two nodes can be determined by the distance between them. Suppose we deal with region as a node of social networks, the spatial proximity between two regions can be derived by a centroid distance or a geometric relationship between them. Some possible criteria of w_{ij}, the measure of the spatial proximity of regions R_i and R_j are as follows (Bailey and Gatrell, 1995; Park, 2004).

$$w_{ij} = \begin{cases} 1 & \text{centroid of } R_j \text{ is one of the } k \text{ nearest centroids to that of } R_i \\ 0 & \text{otherwise} \end{cases}$$

$$w_{ij} = \begin{cases} 1 & \text{centroid of } R_j \text{ is within some specified distance of that of } R_i \\ 0 & \text{otherwise} \end{cases}$$

$$w_{ij} = \begin{cases} d_{ij}^{\gamma} & \text{if inter-centroid distance } d_{ij} < \delta \ (\delta>0;\ \gamma<0) \\ 0 & \text{otherwise} \end{cases}$$

$$w_{ij} = \begin{cases} 1 & R_j \text{ shares a common boundary with } R_i \\ 0 & \text{otherwise} \end{cases}$$

$w_{ij} = \frac{l_{ij}}{l_i}$ l_{ij} is the length of common boundary between R_i and R_j, and l_i is the perimeter of R_i

As a modification of the classical ways of measuring degree and closeness centrality, we propose the GWCMs whereby the interaction intensity and the spatial proximity are optionally involved as a weighting scheme. In the following formulae of degree (D) and closeness (C) centrality, WII stands for "weighed by interaction intensity," and WSP denotes "weighed by spatial proximity."

$$D_{WII}(n_i) = \sum_{j=1}^{g} WII(n_i, n_j)x(n_i, n_j)$$

$$D_{WSP}(n_i) = \sum_{j=1}^{g} WSP(n_i, n_j)x(n_i, n_j)$$

$$C_{WII}(n_i) = \left[\sum_{j=1}^{g} WII(n_i, n_j)d(n_i, n_j)\right]^{-1}$$

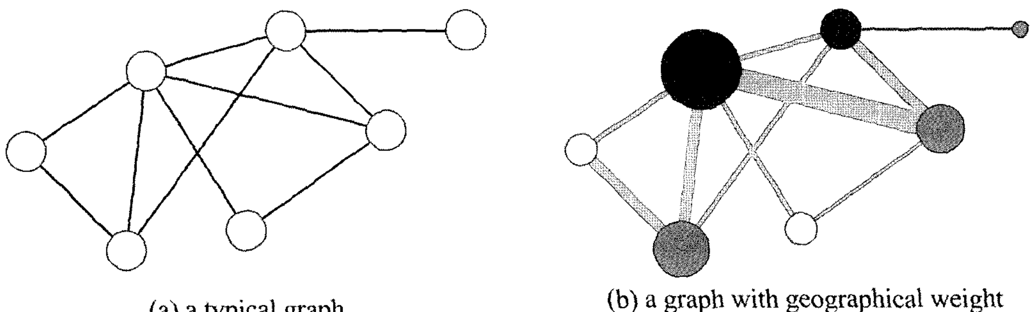
$$C_{WSP}(n_i) = \left[\sum_{j=1}^{g} WSP(n_i, n_j)d(n_i, n_j)\right]^{-1}$$

where n_i is the i-th node; g is the group size; $WII(n_i, n_j)$ is the weight by interaction intensity between n_i and n_j; $x(n_i, n_j)$ is the binary connectivity of network data between n_i and n_j; $WSP(n_i, n_j)$ is the weight by spatial proximity between n_i and n_j; and $d(n_i, n_j)$ is the shortest path length between n_i and n_j in a network graph.

Figure 2 shows that a social network graph using the GWCMs (b) can provide more information about spatial factors than a typical social network graph (a).

3.2 Map-integrated Social Network Graph

As a modification of typical social network graphs, we present MSNG that includes the geographically referenced arrangement of nodes (Figure 3) and the combination of a network graph and a choroplethic map. The geographically referenced location provides information about geographic distributions of nodes and spatial proximity effects among them. In addition, the choroplethic map allows for comparing the centrality measures of network with socioeconomic variables of nodes.



(a) a typical graph

(b) a graph with geographical weight and interaction intensity

Figure 2. Geographical weight and interaction intensity in social network graphs

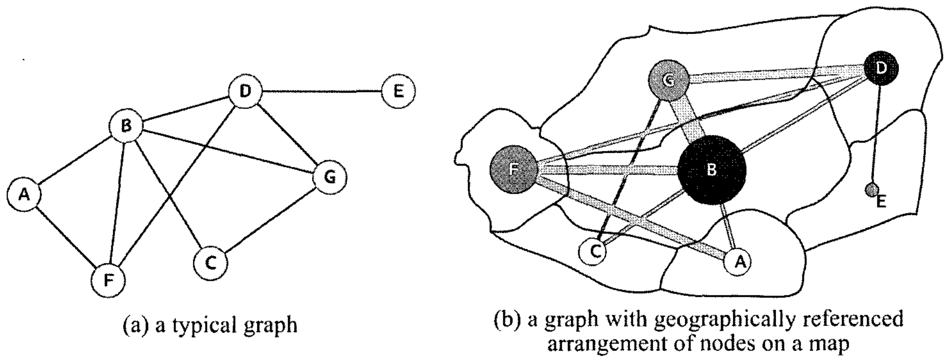


Figure 3. Social network graph with or without geographical reference on a map

3.3 Web-based Visualization Using X3D

Since the renovated social network graph combines several elements for geographical enhancement such as location, degree centrality, closeness centrality, inter-node interaction intensity, and intra-node interaction intensity, its various information can be more effectively represented by a 3D geovisualization. Thus, we employ X3D, the software standard of interactive 3D contents on the Web (Ying *et al.*, 2004; Gelautz *et al.*, 2004; Bouras *et al.*, 2005).

4. An Experimental Demonstration

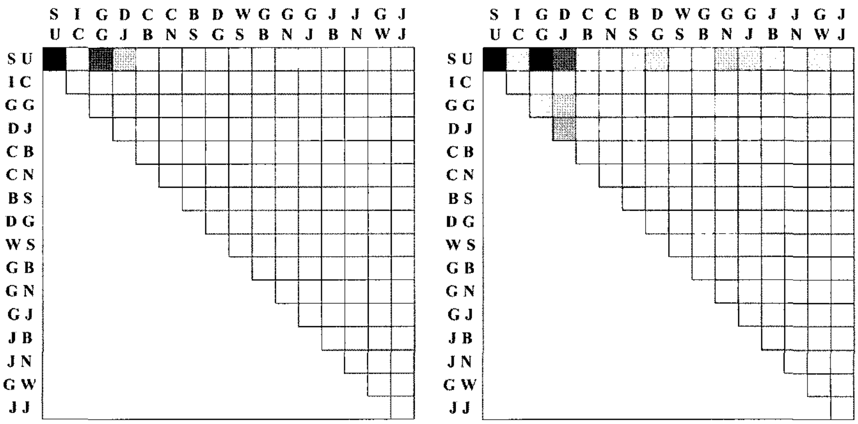
For a case study of visualizing geographical contexts in social networks, we use co-publication data of SCI (Science Citation Index) journal papers by Korean authors in 2004. We classify the data by the locations of co-authors and aggregate them into 16 administrative regions of Korea. With the same dataset, Lee *et al.* (2005) examine R&D networks in Korea and show inter-regional R&D collaboration patterns by using typical social network graphs, which do not adequately visualize geographical information such as location and physical proximity. The X3D visualization of the renovated social network graph presented in this paper can provide more information of geographical contexts in social networks.

4.1 Data Exploration

Table 1 shows a matrix of regional interaction intensity measures in percentage. Every region's inter-node (inter-region) collaboration with Seoul (SU) (the first row in the matrix) is remarkably dominant, and the degree of intra-node (intra-region) collaborations (the numbers in a diagonal direction) is relatively high. The distribution pattern of regional collaboration dominated by a single region (SU) can be easily captured by the simplified grayscale representation of regional interaction intensity diagrams (Figure 4). A contrast enhancement

Table 1. Regional interaction intensity measures

(%)	SU	IC	GG	DJ	CB	CN	BS	DG	WS	GB	GN	GJ	JB	JN	GW	JJ
SU	15.95	2.01	10.87	6.81	1.77	1.61	1.98	2.38	0.40	1.16	2.67	2.27	1.92	0.55	2.27	0.51
IC		0.19	0.69	0.59	0.08	0.16	0.21	0.06	0.04	0.14	0.14	0.13	0.14	0.08	0.09	0.02
GG			2.18	3.01	0.54	0.60	0.94	1.13	0.12	0.45	1.25	0.98	0.55	0.28	0.60	0.14
DJ				4.09	0.84	0.78	1.04	0.75	0.19	0.65	1.33	1.20	1.03	0.37	0.52	0.07
CB					0.18	0.18	0.26	0.15	0.02	0.13	0.16	0.14	0.12	0.07	0.21	0.05
CN						0.12	0.15	0.14	0.00	0.07	0.24	0.19	0.12	0.06	0.18	0.00
BS							1.44	0.46	0.21	0.29	0.79	0.24	0.32	0.16	0.17	0.09
DG								0.44	0.05	0.72	0.50	0.46	0.16	0.02	0.18	0.09
WS									0.02	0.03	0.05	0.00	0.00	0.02	0.01	0.02
GB										0.25	0.29	0.16	0.12	0.04	0.09	0.07
GN											0.97	0.42	0.16	0.30	0.11	0.06
GJ												0.66	0.64	0.30	0.19	0.02
JB													0.68	0.16	0.19	0.08
GN														0.14	0.05	0.01
GW															0.32	0.11
JJ																0.03



(a) linear method (b) square root method

Figure 4. Regional interaction intensity diagrams

technique (Figure 5) can be used in the diagrams for more intuitive capturing of the distribution pattern.

4.2 X3D Visualization of Renovated Social Network Graph

In order to represent geographically enhanced components of the renovated social network graph in a 3D space, we utilize the visualization elements such as X-Y plane, Z-axis, symbol size, symbol darkness, and line width. Geographic location can be assigned to X-Y plane, and inter-node interaction intensity would be represented by the width of connected lines. The other elements such as degree centrality,

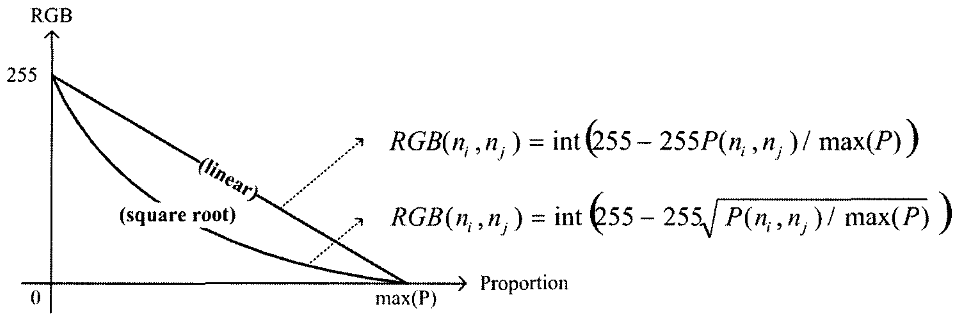


Figure 5. RGB conversion and contrast enhancement for regional interaction intensity diagrams

closeness centrality, and intra-node interaction intensity could be arbitrarily assigned to Z-axis, symbol size, or symbol darkness. The renovated social network graph can include a choroplethic chart map to provide additional socioeconomic information of nodes as a reference for the centrality measures.

In the renovated social network graph of Figure 6, the intra-node interaction intensity is demonstrated by symbol darkness; the degree centrality weighted by interaction intensity (D_{WII} with the portion of inter-regional co-

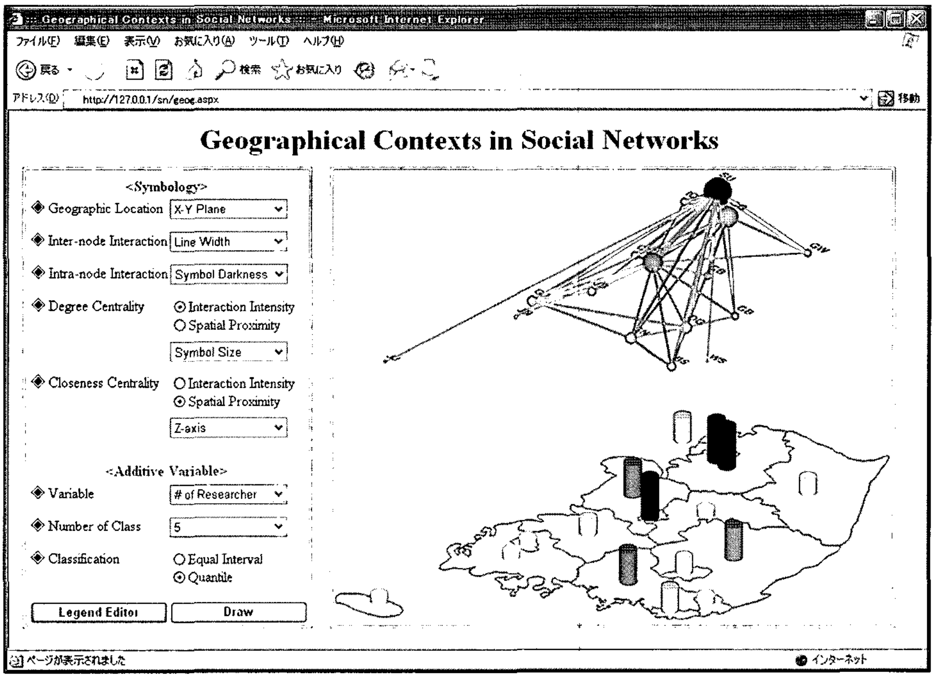


Figure 6. Visualization of a renovated social network graph

publication) is represented by symbol size; the closeness centrality weighted by spatial proximity (C_{WSP} with a w_{ij} using the ratio of inter-centroid distance) is represented by Z-axis; and the choroplethic chart map is provided to show the number of researchers in each region as an additive socioeconomic variable. As expected from the data exploration, Seoul shows very high degree and closeness centrality as well as inter- and intra-node interaction intensity. The graph shows that Seoul is distinctively high in the closeness centrality weighted by spatial proximity, although its spatial proximity measure is not the highest among the 16 nodes. Presumably, other factors of Seoul, such as concentration of highly educated people, research universities, and R&D investments, overwhelm the effects of distance decay in the R&D networks of Korea.

5. Concluding Remarks

In this paper, we focus on the geographical contexts in social networks which typical social network analyses have not paid much attention to. We propose a method to adequately represent the geographical contexts in social networks through GWCMs and MSNG. The GWCMs reflect the differences in interaction intensity and spatial proximity among nodes, and the MSNG incorporates the GWCMs and the geographically referenced arrangement of nodes on a choroplethic map. We also demonstrate a renovated social network graphy on the Web, using the co-publication data of SCI journal papers. The suggested approach would support the findings from an analysis of regional interactions in social networks. It can enrich its applicabilities by integrating "the geographies with the social."

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