A Procedural Framework for GraphML-based Closeness Centrality Representations on Workflow-Supported Enterprise Social Networks

Min-Joon Kim[1], Hyun Ahn[2], and Minjae Park[3]
[1] School of Integrated Technology, Yonsei University
Incheon, South Korea
[e-mail: minjoon@yonsei.ac.kr]
[2] Department of Computer Science, Kyonggi University
Suwon, South Korea
[e-mail: hahn@kgu.ac.kr]
[3] Engineering Innovation Department, R&D Center, BISTel, Inc.
Seoul, South Korea
[e-mail: mjpark@bistel-inc.com]
*Corresponding author: Minjoon Kim

Abstract

In this paper, we build a theoretical framework for quantitatively measuring and graphically representing the degrees of closeness centralization among performers assigned to enact a workflow procedure. The degree of closeness centralization of a workflow-performer reflects how near the performer is to the other performers in enacting a corresponding workflow model designed for workflow-supported enterprise operations. The proposed framework comprises three procedural phases and five functional transformations, such as discovery, analysis, and visualization phases, which carry out ICN-to-WsoN, WsoN-to-SocioMatrix, SocioMatrix-to-DistanceMatrix, DistanceMatrix-to-CCV, and CCV-to-ccGraphML transformations. We develop a series of algorithmic formalisms for the procedural phases and their transformative functionalities, and verify the proposed framework.

***Keywords*:** workflow-supported enterprise social network, information control net (ICN), closeness centralization measures/vector, workflow model, graph markup language (graphML), organizational knowledge management, workflow intelligence

1. Introduction

The workflow model is concretized through multiple-level abstraction[13], such as view, conceptual, and physical levels of abstraction, to provide a series of theoretical bases for designing and implementing a workflow management system. The typical view-level abstract is the information control net[15], which is a formal way of specifying a workflow procedure particularly focus- ing on the control flow aspect of activities. The conceptual-level abstract is a various formation of transformations according to the essential aspects of the workflow procedure like performer-dependency, control-dependency, role-dependency, and data-dependency aspects. The physical-level abstract of a workflow procedure represents the

architectural distribution of its activities in realizing a workflow management system. The scope of this paper conceives a series of theoretical formalisms related with conceptual-level abstract of the workflow model, particularly focusing on the performer-dependency aspect. Recently, workflow modeling techniques[13], organizational intelligence tech- niques[25][19], and social network analysis techniques[16] are converging on "*workflow-supported people*," which starts from the strong belief that so- cial relationships and collaborative behaviors among people, who are involved in enacting a workflow procedure, affect the overall performance as well as the degrees of working productivity in performing the real business operations under the control of workflow-supported organizations[23]. As a consequence, research and development issues [1][21][20][14][9][22] of converging the concept of social network and its analysis methods upon workflow-supported people (so-called workflow-performers) have been emerging in the literature.

Our key contribution in this paper is to propose a theoretical framework and its related formalisms for measuring how much close to other workflow- performers by using the social network analysis techniques, particularly the closeness centrality analysis formulas[16]. The centralization of workflow-performers is a typical social network analysis technique identifying the important or prominent performers within a workflow procedure by summarizing the structural relationships among all the performers. The most widely used central- ization measures are degree, closeness, betweenness, and eigenvalue. These measures vary in their applicability to non-directed and directed relations, and differ at the individual performer and the group performers of the partial or complete workflow procedure levels. In this paper, we confine the scope of the measurements to the closeness centralization measurement for individual and group workflow-performers within a workflow procedure. The eventual goal of the framework is to numerically measure and calculate the degree of work-intimacy and collaboration among all performers involved in a workflow model or a workflow package (a group of inter-relevant workflow models) on a workflow-supported organization.

2. Conceptual Backgrounds

We are particularly interested in adopting the concept of closeness centrality to measure the degree of work-intimacy and collaboration among performers in enacting a corresponding workflow model. The concept was originally developed to reflect how near a node is to the other nodes in a social network, and so the semantic significance of closeness and distance refer to how quickly an actor can interact with others. In the domain of workflow-supported organizational knowledge, the performer's closeness centralization concept can be interpreted as the extent to how much close a specific performer is to the others on a flow of works. The activity-performer associations eventually form a flow of works among the workflow-performers, which can be represented by the actor-based workflow model[13] or the workflow-supported social network model[10], both of which were proposed by the authors' research group. Then, on a workflow-supported social network, it might be quite in the nature of things to raise the questions as followings:

- Who is the most important or prominent performer(s) interacting the most tightly with others in enacting a specific workflow procedure?
- How near is the most prominent performer to others in a workflow-supported enterprise social network?
- What is the average distance (or closeness) among performers in a workflow-supported enterprise social network? In other words, how quickly can a performer interact with others in enacting the associated workflow procedure by communicating directly or through very few intermediaries?

Conclusively, the answers to the questions ought to be able to convey a very valuable and meaningful insight to the workflow-supported organization. The primary rationale of the closeness centralization concept is on the questions and answers section. A theoretical framework to be expatiated in the next consecutive sections of this paper covers from discovering a shape of workflow-performers' collaborative relationships through a workflow-supported enterprise social network to analyzing their closeness centralization measures by mathematically extending some of the well-known closeness centrality formulas [16] in

the social network analysis literature. Ultimately, the theoretical framework can be implemented as an organizational intelligent system that is able to quantitatively answer to the questions through the closeness centralization concept and measurement, closeness-centrality, at both individual and group levels of the workflow-supported organization.

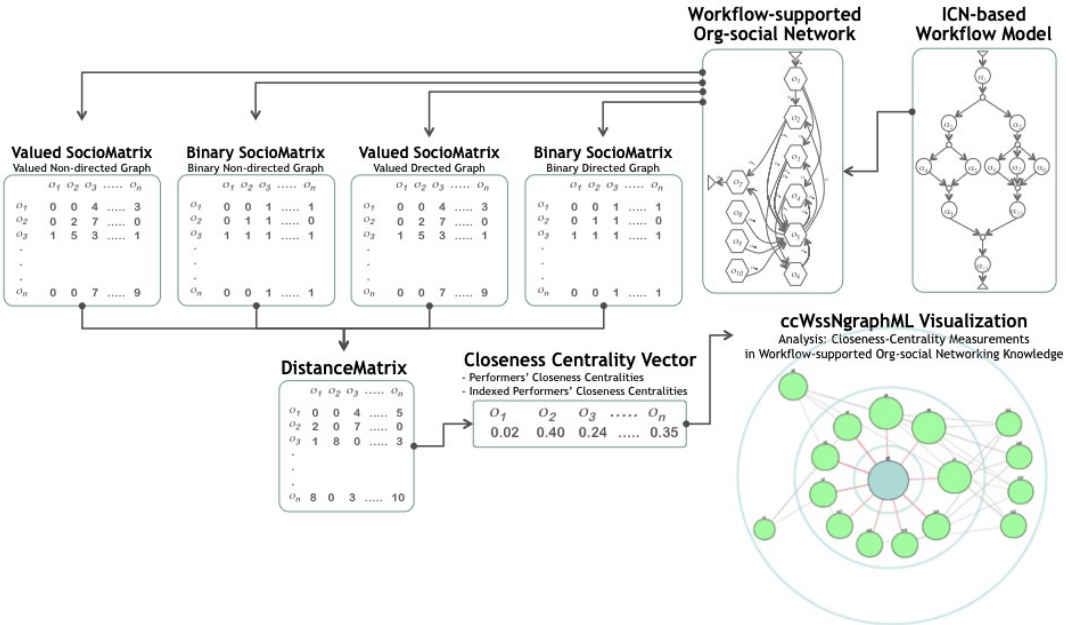

Fig. 1. A Procedural Framework for Workflow-Performers' Closeness Centrality Representations

3. A Procedural Framework

In this section, we expatiate on a theoretical framework for measuring the closeness centralizations that enable us to quantify the levels of work-intimacy and collaboration among workflow-performers. The framework is a kind of procedural framework that comprises three stepwise phases with five functional transformations, as illustrated in **Fig. 1**. The phases are discovery, analysis, and visualization phases with the following functional transformations:

– Discovery Phase
- ICN-to-WsoN Transformation: Building a workflow-supported enterprise social network model from an information control net.
- WsoN-to-SocioMatrix Transformation: Constructing four types of SocioMatrices from a workflow-supported enterprise social network model.

– Analysis Phase
- SocioMatrix-to-DistanceMatrix Transformation: Creating a DistanceMatrix from a SocioMatrix by applying the geodesic (shortest) distance formulas.
- DistanceMatrix-to-CCV Transformation: Building up a closenesscentrality vector on the DistanceMatrix by applying the closeness centrality formulas.

– Visualization Phase
- CCV-to-ccGraphML Transformation: Generating a closeness centralization graph formatted in ccGraphML from the closeness centralization vector.

3.1 The Discovery Phase

We start from introducing the basic concept and definition of a performer-flow graph that enables us to efficiently calculate the closeness centralization measurements. The performer-flow graph is discovered by analyzing workflow-performers' associative relationships with activities in a workflow procedure. For the sake of the closeness centralization measurements, the performer-flow graph needs to be represented by a theoretical notation as well as a mathemat- ical notation. This graph's formal representation is defined by the workflow-supported enterprise social network

model[20][14][10], which is abbreviated as WsoN, and its mathematical representation is a form of matrix, which is called SocioMatrix[16]. In consequence, the discovery phase of the performer-flow graph from an information control net consists of two of these functional transforma- tions, such as the ICN-to-WsoN Transformation and the WsoN-to-SocioMatrix Transformation

1) The ICN-to-WsoN Transformation: The purpose of this transformation is to functionally generate a performer-flow graph from an information control net. The performer-flow graph is formed through the activity-performer associations that can be transitively obtained from the activity-role associations and the role-performer associations in the information control net, as followings:

- The activity-role association: for any activity (α), $\{\alpha|\varepsilon_p(\alpha)=\{\eta_i\} \wedge \eta_i \in P\}$, where P is the set of roles, $\{\eta_1, \eta_2, \ldots, \eta_n\}$, means that the activity α is associated with a single role out of P ; also, for any role(η), $\{\eta \mid \varepsilon_a(\eta) = \{\alpha_s, \ldots, \alpha_m\} \wedge \{\alpha_s,\ldots,\alpha_m\} \subset A\}$, where A is the set of activities, $\{\alpha_1,\alpha_2,\ldots,\alpha_m\}$, means that the role η is associated with one or more activities out of A. Summarily, activity-to-role association is one-to-one relationship, whereas role-to-activity association is one-to-many relationship.
- The role-performer association: for any role (η), $\{\eta|\pi_c(\eta)=\{ø_s,\ldots,ø_k\} \wedge \{ø_s,\ldots,ø_k\} \subset C\}$, where C is the set of performers, $\{ø_1,ø_2,\ldots,ø_n\}$, means that the role η is associated with one or more performers out of C; also, for any performer(ø), $\{ø|\pi_p(ø)=\{\eta_s,\ldots,\eta_m\} \wedge \{\eta_s,\ldots,\eta_m\} \subset P\}$, where P is the set of roles, means that the performer ø is associated with one or more roles out of P. Summarily, both role-to-performer association and performer-to-role association are many-to-many relationships.
- Based upon these two types of associations, we are able to transitively obtain the activity-performer associations from an information control net, and we know that both the activity-to-performer association and performer-to-activity association are many-to-many relationships. Conclusively speaking, not only more than one performers can participate in enacting an activity, but also a performer is able to participate in enacting one or more activities.

2) The WsoN-to-SocioMatrix Transformation: The performer-flow graph is formally represented by the workflow-supported enterprise social network model, and its mathematical representation is expressed in terms of SocioMatrix[16] introduced in the social network literature. In order to mathematically measure the closeness centralizations, the performer-flow graph needs to be transformed in SocioMatrix by a WsoN-to-SocioMatrix trans- formation algorithm. SocioMatrix can be refined on two groups of subtle ma- trices—binary directed/undirected SocioMatrix and valued directed/undirected SocioMatrix. We use to construct a sociogram[16] that is a two-dimensional diagram for depicting the precedence relationships among performers. The term, directed, indicates the directed-precedence relationships or ties from one at the tail to another at the arrowhead, whereas the term, undirected (no arrowheads), implies mutual-precedence relationships. Likewise, when a directed/undirected performer-flow graph is transformed to SocioMatrix, the term, binary, implies the most basic measurement, presence or absence of a tie, which is a dichotomy indicated by the binary value of 1 or 0, respectively; also SocioMatrix may include valued cells, reflecting the intensity of relationships or ties, such as frequency of performer-flows, tie strength, or magnitude of associations, and therefore the cell entries in SocioMatrix can vary from 0 to the maximum level of dyadic interactions.

3.2 The Analysis Phase

As stated in the conceptual background section, we are interested in quantitatively measuring the degree of closeness centralization by borrowing the well-known formulas[16] in the social network analysis literature. The analysis phase carries out two functional transformations. One is the SocioMatrix-to-DistanceMatrix transformation to calculate the geodesic distances among performers, and the other is the Distance-to-CCV transformation to measure the individual closeness centralizations by using the result (the geodesic distances) of the former transformation. The ultimate goal of the analysis phase aims to answer to the following essential question:

– How quickly can a performer interact with others in enacting the associated workflow procedure by communicating directly or through very few intermediaries?

That is, through the closeness centrality concept and its measurements we can obtain a reasonable level of analysis results, which is enough to answer to the above question as well as the other questions stated in the beginning of the paper. The closeness centrality measures can be applied to the individual performer (*individual closeness centrality*) as well as the group of performers (*group closeness centrality*).

1) The SocioMatrix-to-DistanceMatrix Transformation: we are able to calculate the closeness centrality measures by applying the formula given in (1) [16]

– The Index of Individual Closeness Centrality

$$C_C(\varnothing_i) = \frac{1}{\left[\sum_{j=1}^{N} d(\varnothing_i, \varnothing_j)\right]} (i \neq j) \quad (1)$$

Formula (1) is for measuring an individual performer's closeness centrality. The term, $d(\varnothing_i,\varnothing_j)$, in the denominator is a function of geodesic distance that is the length of the shortest path out of all reachable paths from $\varnothing_i$ to $\varnothing_j$. The conceptual implication of the individual closeness centrality refers to how quickly a performer can interact with others by communicating directly or through very few intermediaries. Conclusively, from one of the SocioMatrices with N performers, the index of individual closeness centrality is computed as the inverse of the sum of the geodesic distances between performer i and the (N − 1) other performers. The SocioMatrix-to-DistanceMatrix transformation is charged with the function of geodesic distances, $d(\varnothing_i,\varnothing_j)$, for all workflow-performers by iteratively applying the function for N times as many workflow- performers.

2) The DistanceMatrix-to-CCV Transformation: Based on the geodesic distance matrix, DistanceMatrix[N,N], transformed from the SocioMatrix-to-DistanceMatrix transformation function, we eventually measure the closeness centralizations of all the individuals. The following formula (2) is for carrying out the DistanceMatrix-to-CCV transformation. The re-sult of the transformation is the closeness centrality vector, $[C_C(\varnothing_1), \ldots, C_C(\varnothing_n)]$. Each quantity of the vector is computed as the inverse of the sum of the geodesic distances between its corresponding performer, $\varnothing_i$, and the (N − 1) other performers. As you see, the measured indices computed from formula (2) can never be 0.0, because division by zero is mathematically undefined. Thus, the index of individual closeness centrality cannot be computed for an iso- lated performer, which is the case of that only a single performer is assigned to enacting all activities of the corresponding workflow procedure. Also, we can predict that the lowest index, which is the case of the highest sum of the geodesic distances between a focal performer and others, comes out from a performer either in a relatively large network or in a small network with relatively long geodesic distances from others.

– The Closeness Centrality Vector

$$\left[C_C(\varnothing_i)\right]_{i=1}^{N} = \left[\frac{1}{\sum_{j=1}^{N} DistanceMatrix[\varnothing_i, \varnothing_j]}, (i \neq j)\right]_{i=1}^{N} \quad (2)$$

– The Standardized Closeness Centrality Vector

$$\left[C_C^S(\varnothing_i)\right]_{i=1}^{N} = \left[(N-1) \cdot C_C(\varnothing_i)\right]_{i=1}^{N} \quad (3)$$

Formula (3) is for standardizing the index of individual closeness centrality by multiplying by (N − 1), in which the corresponding performer is excluded from the total number of performers. Suppose that an individual performer has the closest distance to all others, which means that the performer has a direct tie to everyone in the network. Then, the computed index values will be vary according to their network sizes. In order to control the size of the network, it is necessary for the individual index to be standardized between 0.0 (even then it is never happened) and 1.0. It allows, so, meaningful comparisons of performers' closeness centralities across different sizes of workflow-supported enterprise social networks.

3) Group Closeness Centrality: As the last step of the analysis phase, we remain one more additional transfor- mation to quantify the network-wide degree of closeness centralization, which we would call the sCCV-to-GCC transformation. The network-wide degree of closeness centralization measurement is to quantify the degree of dispersion indicating the hierarchy of closeness centralities within a workflow-supported enterprise social network.

In other words, this measure implies the extent to which performers in a given network differ in their closeness centralities, and it can be calculated by the formula[16] of the index of group closeness centrality as followings:

– The Index of Group Closeness Centrality

$$GC_C = \frac{\sum_{i=1}^{N} \left[C_C^S(ø^*) - C_C^S(ø_i) \right]}{\frac{(N-2)(N-1)}{(2N-3)}} \quad (4)$$

In formula (4), $C_C^S(ø^*)$ denotes the highest standardized individual close- ness centrality measure observed in a given network, and $C_C^S(ø_i)$ is the stan- dardized individual closeness centrality measure of each of the (N − 1) other performers. The maximum value of the index of group closeness centrality ought to be 1.0 when the corresponding network forms completely an uneven dispersion in the standardized individual closeness centrality measures, which is in the case of that a single performer has the maximum measure and all others have the minimum. In contrast, the index of group closeness centrality equals to 0.0 in the case of that every performer has the same individual close- ness centrality measure. Conclusively, the index of group closeness centrality in a workflow-supported enterprise social network ought to be between 0.0 and 1.0. The closer that the index value is to 1.0, the more uneven or hierarchical is the closeness centralizations of performers in a given network; while on the other hand, the closer the index value is to 0.0, then the more the closeness central- ization of the network is evenly dispersed. We would provide the algorithm of the sCCV-to-GCC transformation because of its simple and straightforward logic.

3.3 The Visualization Phase

As stated in the introductory statements of the framework, we are particularly interested in visualizing the degree of closeness centrality of every workflow performer associated with a specific workflow-supported enterprise social network. The last phase of this theoretical framework is just the visualization phase carrying out the CCV-to-ccGraphML transformation. In order to visualize the quantities of the closeness centrality vector, we devise an XML schema of the WsoN-ccGraphML by revising the WsoN-GraphML[24], which is based on the well-known XML-based graphical markup language, GraphML. The CCV-to- ccGraphML transformation function, so, generates a ccGraphML-based textual form from the closeness centrality vector, $[C_C(ø_1),...,C_C(ø_n)]$, measured in the previous analysis phase.

As depicted in **Fig. 2**, the XML schema of the proposed ccGraphML is able to basically express the graphical magnitude and color of the individual closeness centrality as well as three types (in-degree, out-degree, and full-degree) of close- ness centralities on each workflow-performer. Originally, the graph markup language, GraphML, is an XML-based graph definition language comprising nodes and edges. The nodes and edges are represented by the key attributes defined in the tags of <Node Keys> and <Edge Keys>, respectively. Each node is identified by node-id and node-color, whereas edges distinguish each other through the attributes of edge-id, edge-color, source-node, and target- node. Also, the graph itself can be characterized by graph-type attribute as either undirected graph or directed graph. In order to sophisticatedly describe the workflow-supported enterprise social network by using GraphML, ccGraphML supplemented the domain-specific attributes to <Node Keys> and <Edge Keys> as shown in the righthand side of **Fig. 2**. Especially, to graphically reflect the strengths of the relationships (or work-intimacies) between workflow perform- ers, we adopt the attribute of Weight as <Edge Keys>. **Fig. 3** is the ccGraphML contents of the performer-flow graph spawned from the hiring workflow procedure[15], and a screen-snapshot captured from a visualization system[11] that is developed through the proposed framework, where shows the visual representation of the individual closeness centrality measures centered from the performer, $ø_5$, who has the highest closeness centrality measure.

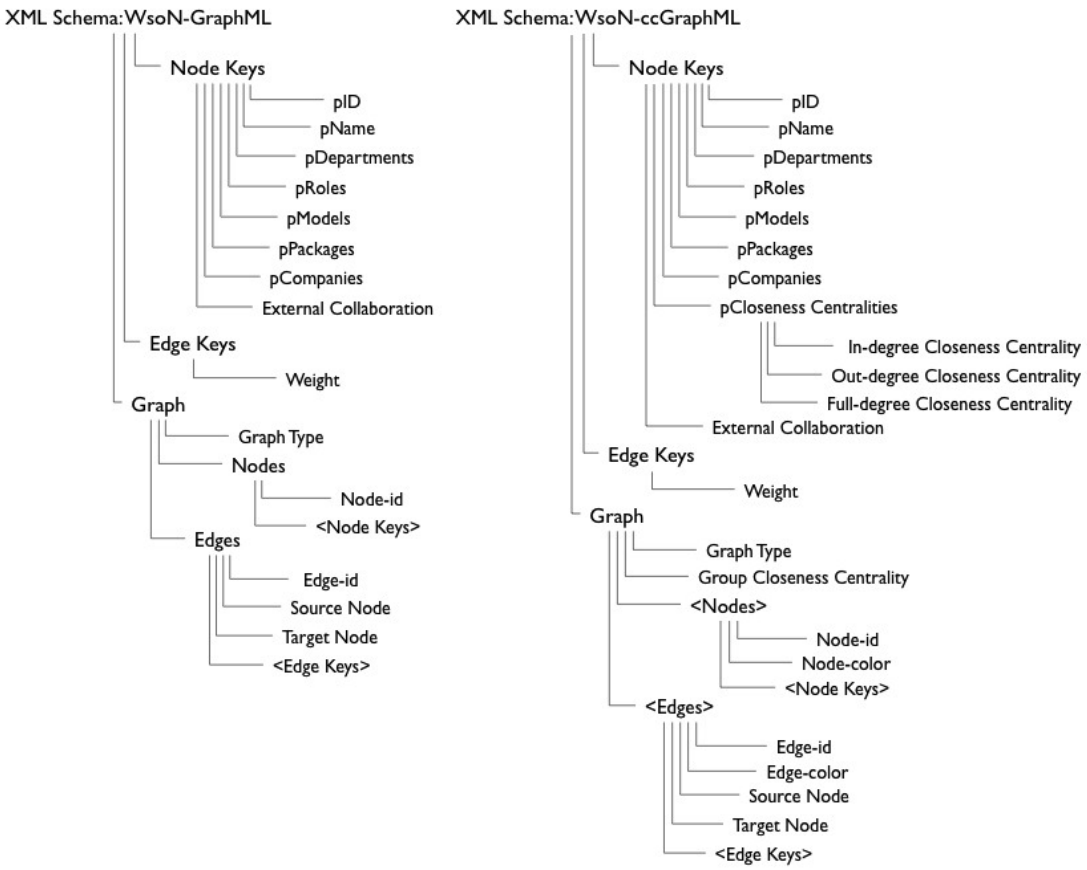

Fig. 2. WsoN's GraphML Schema and ccGraphML Schema for Closeness Centrality

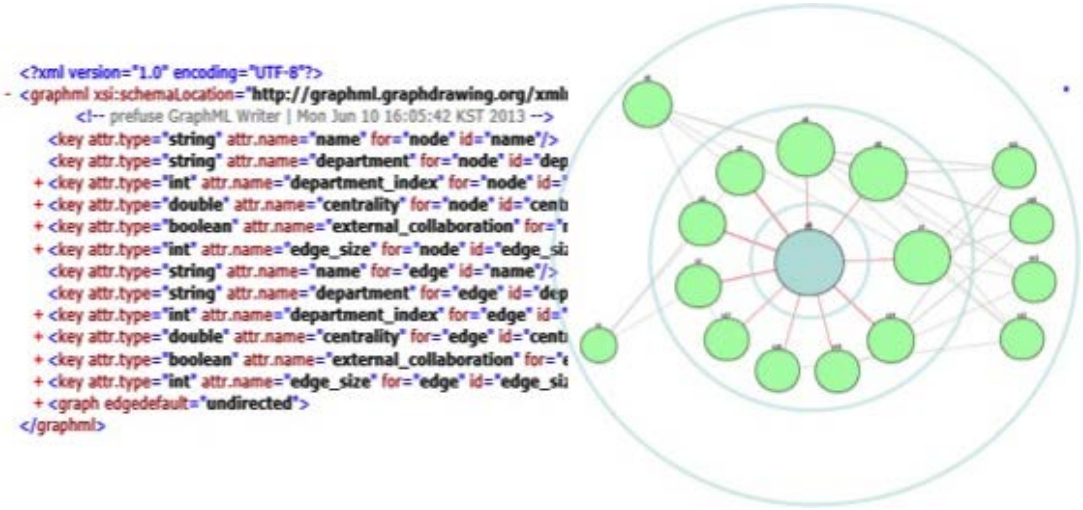

Fig. 3. Closeness Centrality Visualization with ccGraphML for the Performer, $ø_5$

4. Related Works

Recently, workflow literature has just begun to focus on social and collabo- rative structures on process-oriented organizations. The relationship between knowledge management and organizational performance has been the sub- ject of discussion in management literature, and some results[8][4][2] found out that there is a significant link between human-centered structural knowl- edge and organizational culture and performance. Our work of the theoreti- cal framework is one of the pioneering activities for digging up new method- ologies and techniques—discovery, analysis, and visualization—for workflow- supported org-social networking knowledge management. This section gives the descriptions of the research statuses and surveys related to each of these issues.

1) Discovery Issue: In order to carry out the closeness centralization mea- surement, we need to project the human-centered associative knowledge from a workflow procedure, and transform it to a form of human-centered graph so as to be mathematically analyzed. The performer-flow graph formally rep- resented by the workflow-supported org-social network model is to be pro- posed with this intention in the paper, and we have addressed this human-centered transformation issue as "workflow-supported enterprise social networking knowledge discovery issue." This issue can be subdivided into two branches of research approaches—discovery issue and rediscovery issue. The rediscovery issue stems from the workflow mining issue that tries to explore human be- havioral knowledge (enacted org-social networking knowledge) from workflow enactment event logs, whereas the discovery issue is related with exploring various human-centered associative knowledge (planned org-social networking knowledge) from the growing pile of workflow models and packages. A typical research publication concerning the rediscovery issue might be [1], in which the authors built a methodology and system to rediscover org-social networking knowledge from the petri-net based workflow enactment event logs. Also, many research groups pointed out the necessity of rediscovering the performer or human behaviors from workflow enactment event logs through those publications, [21][25][6][19], so far. Also, the org-social networking knowledge discovery is- sue was firstly addressed by the authors' research group through proposing a theoretical framework in [20] and implementing the framework in [14]. In this paper, we have refined the org-social networking knowledge discovery al- gorithm proposed in [13][20][10], and we efficiently transform the discovered org-social networking knowledge to a form of the performer-flow graph so as to be efficiently applied for the closeness centralization measurements.

2) Analysis Issue: After either discovering or rediscovering the workflow-supported org-social networking knowledge, we need to analyze the knowl- edge and quantify the analyzed results in order to exert valuable, meaningful, and worth knowledge on workflow-supported organizations. The literature has been trying to solve this analysis issue by two approaches, so far. One is to use the traditional statistical analysis techniques[25], the other is to employ the sophisticated social network analysis techniques already proved in the social science domain and summarily introduced in [16] and [5]. [25] tried to build a fundamental theory for discovering organizational work-sharing networks, such as role-based organizational work-sharing network and human-based or- ganizational work-sharing network, from a specific workflow procedure, and suggested a new statistical analysis approach for statistically quantifying the degree of organizational work-sharing and collaboration. [16] and [5] elaborated on the social network analysis techniques and the affiliation network analysis techniques, respectively. Note that the affiliation network is a special type of the social network. The authors' research group has employed these so- phisticated social network analysis techniques, such as centrality, prestige, and clique techniques, to analyze the workflow-supported org-social networks[10] and affiliation networks[9] explored by the discovery methodologies. In par- ticular, we have been actively adopting the centrality technique in analyzing the workflow-supported org-social networking knowledge, so far. the centrality technique is subdivided into degree centrality[10], closeness centrality[22][3], betweenness centrality[12], and eigenvalue centrality so as to be elaborately applied into a

real organizational world. As one of those efforts, in this pa- per, we have tried to conceive the algorithmic and procedural framework of closeness centralization measurements and suggested a theoretical guidance to quantitatively analyze and compare the degrees of closeness and prominence among workflow-performers in enacting a workflow procedure.

3) Visualization Issue: Until now, almost all research and development ac- tivities are mainly concerned about how to represent, discover, and analyze the workflow-supported org-social networking knowledge, as mentioned previ- ously, whereas the literature is rarely interested in how to effectively, efficiently, and even beautifully visualize the discovered or/and analyzed knowledge. The only one emphasizing the visualization of the knowledge and its analyzed re- sults was [11], in which the authors developed a display function to visualize the degree centralization measurements of the performers engaged in enacting a workflow model. However, because the display function is able to visualize the graphical objects on a fixed-size window and it doesn't adopt any graphical toolkits or libraries[17][7][18], it always needs a certain amount of additional manual-operations, such as re-positioning, resizing, or re-arranging operations, to gracefully and properly beautify the graphical objects making up the displayed workflow-supported org-social network. Therefore, as a upgraded version of [11], this paper proposes a theoretical approach to dramatically improve the quality of beautification as well as the quality of efficiency in visualizing the closeness centralization measures. The theoretical approach devised a schema formatted in the extended XML-based graph markup language[24], ccGraphML, so as to graphically express the closeness centrality vector by adopting the well-known information visualization toolkits[7] like Prefuse, JFreeChart, and Log4j.

5. Conclusions

In this paper, we suggested a theoretical way of discovering, analyzing, and visualizing the closeness centralization measures that are quantitatively expressing the prominence and collaborative behaviors among workflow-supported performers in enacting a workflow procedure. That is, we have built, so far, a theoretical framework for quantitatively and graphically measuring the degrees of closeness centralization among performers assigned to enact a work- flow procedure. The proposed framework supports the three procedural phases, discovery, analysis, and visualization phases, during which they carry out five functional transformations, ICN-to-WsoN, WsoN-to-SocioMatrix, SocioMatrix-to-DistanceMatrix, DistanceMatrix-to-CCV, and CCV-to-ccGraphML transformations. We have also developed a series of algorithmic formalisms and verified them through an operational example. As a consequence, we would summarily conclude by showing that the theoretical framework is able to answer to the questions as follows:

– Who is the most important or prominent performer(s) interacting the most tightly with others in enacting a specific workflow procedure? Answer: the performer whom has the highest quantity in the close- ness centrality vector or the standardized closeness centrality vector, Maximum ($C_C(ø_1)$,...,$C_C(ø_n)$).

– How near is the most prominent performer to others in a workflow-supported enterprise social network? Answer: the geodesic distances from the most prominent performer to others in the geodesic distance matrix, DistanceMatrix[N,N].

– What is the average distance (or closeness) among performers in a workflow-supported social network? In other words, how quickly can a performer interact with others in enacting the associated workflow procedure by communicating directly or through very few intermediaries? Answer: the index of group closeness centrality, GC_C.

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References

[1] Wil M. P. van der Aalst, et al., "Discovering Social Networks from Event Logs," COMPUTER SUPPORTED COOPERATIVE WORK, Vol. 14, No. 6, pp. 549-593 (2005)

[2] Stephan Aier, "The Role of Organizational Culture for Grounding, Management, Guidance and Effectiveness of Enterprise Architecture Principles," Information Systems and e-Business Management, Volume 12, Issue 1, pp. 43-70 (2014)

[3] Alyeksandr Battsetseg, et al., "Organizational Closeness Centrality Analysis on Workflow-supported Activity-Performer Affiliation Networks," Proceedings of 2013 IEEE International Conference on Advanced Communications Technology, Pheonix Park, Pyeongchang, South Korea, pp. 154-157 (2013)

[4] Shu-Hui Chuang, Chechen Liao, Shinyi Lin, "Determinants of Knowledge Management with Information Technology Support Impact on Firm Performance," Information Technology and Management, Volume 14, Issue 3, pp. 217-230 (2013)

[5] Katherine Faust, "Centrality in Affiliation Networks," Journal of Social Networks, Vol. 19, pp. 157-191 (1997)

[6] E. Ferneley, R. Helms, "Editorial of the Special Issue on Social Networking," Journal of Information Technology, Vol.25, No.2, pp. 107-108 (2010)

[7] Jeffrey Heer, Stuart K. Card, James A. Landay, "prefuse: A Toolkit for Interactive In- formation Visualization," Proceedings of 2005 ACM International Conference on CHI, Portland, Oregon, USA (2005)

[8] James H. Kaufman, Stefan Edlund, Daniel A. Ford, Calvin Powers, "The Social Contract Core," ELECTRONIC COMMERCE RESEARCH, Volume 5, Issue 1, pp. 141-165 (2005)

[9] Haksung Kim, et al., "A Workflow Affiliation Network Discovery Algorithm," ICIC Express Letters, Vol.6, No.3, pp. 765-770 (2011)

[10] Myounghoon Jeon, et al., "A Workflow-supported Social Network Model," Proceedings of the ACIS/JNU International Conference on Computer, Networks, Systems, and Industrial Engineering, Jeju Island, South Korea, May 23-25, pp. 457-461 (2012)

[11] Hyeonil Jeong, et al., "A Workflow-supported Social Networking Knowledge Visualization System," Proceedings of the 5th International Conference on Internet, Pattaya, Thailand, pp.187-193 (2013)

[12] Hyeonil Jeong, et al., "Betweenness Centralization Analysis Formalisms on Workflow-Supported Org-Social Networks," Proceedings of 2014 IEEE International Conference on Advanced Communications Technology, Pheonix Park, Pyeongchang, South Korea (2014)

[13] Kwanghoon Kim, et al., "Actor-oriented Workflow Model," Proceedings of the 2nd international symposium on Cooperative Database Systems for Advanced Applications, Wollongong, Australia, March 27-28, pp. 163-177 (1999)

[14] Kwanghoon Kim, "A Workflow-based Social Network Discovery and Analysis System," Proceedings of the International Symposium on Data-driven Process Discovery and Analysis, Campione d'Italia, Italy, June 29-July 1, pp. 163-176 (2011)

[15] Kwanghoon Kim, Clarence A. Ellis, "Section II / Chapter VII. An ICN-based Workflow Model and Its Advances," Handbook of Research on BP Modeling, pp. 142-172, IGI Global, ISR, pp. 142-172 (2009)

[16] David Knoke, Song Yang, SOCIAL NETWORK ANALYSIS - 2nd Edition, Series: Quantitative Applications in the Social Sciences, SAGE Publications (2008)

[17] Anita Komlodi, et al., "An Information Visualization Framework for Intrusion Detection," Proceedings of 2004 ACM International Conference on CHI, Vienna, Austria, pp. 1743-1746 (2004)

[18] Michael Meyer, Tudor Girba, Mircea Lungu, "Mondrian: An Agile Information Visualization Framework," Proceedings of 2006 ACM International Conference on SOFTVIS, Brighton, United Kingdom, pp. 135-144 (2006)

[19] Miha Skerlavaj, Vlado Dimovski, Kevin C Desouza, "Patterns and structures of intra-

organizational learning networks within a knowledge-intensive organization," Journal of Information Technology, Vol. 25, No. 2, pp. 189-204 (2010)

[20] Jihye Song, et al., "A Framework: Workflow-based Social Network Discovery and Analysis," Proceedings of the 4rd International Workshop on Workflow Management in Service and Cloud Computing, Hongkong, China, pp. 421-426 (2010)

[21] Harri Oinas-Kukkonen, et al., "Social Networks and Information Systems: Ongoing and Future Research Streams," JOURNAL OF THE ASSOCIATION OF INFORMATION SYSTEMS, Vol. 11, Issue 2, pp. 61-68 (2010)

[22] Sungjoo Park, et al., "A Closeness Centrality Analysis Algorithm for Workflow- supported Social Networks," Proceedings of 2013 IEEE International Conference on Advanced Communications Technology, Pheonix Park, Pyeongchang, South Korea, pp. 158- 161 (2013)

[23] Stephan Poelmans, Hajo A. Reijers, Jan Recker, "Investigating the Success of Operational Business Process Management Systems," Information Technology and Management, Volume 14, Issue 4, pp. 295-314 (2013)

[24] Ilkyeun Ra, et al., "ccWSSN-GraphML: An Extended Graph Markup Language for Visualizing Closeness-centrality Measurements of Workflow-supported Org-social Networks," Proceedings of KSII the 8th Asia Pacific International Conference on Information Science and Technology (APIC-IST), Jeju Island, South Korea, pp. 97-100 (2013)

[25] Jaekang Won, "A Framework: Organizational Network Discovery on Workflows," Ph.D. Dissertation, Department of Computer Science, KYONGGI UNIVERSITY (2008)