Technological Forecasting & Social Change 80 (2013) 944–955

Contents lists available at SciVerse ScienceDirect

Technological Forecasting & Social Change

Social network analysis of patent infringement lawsuits

Hyoungshick Kim [a], JaeSeung Song [b,*]

[a] Department of Computer Science and Engineering, Sungkyunkwan University, Suwon, Korea
[b] NEC Europe Ltd., Network Research Division, Kurfürsten-Anlage 36 69115, Heidelberg, Germany

A R T I C L E I N F O

Article history:
Received 29 December 2011
Received in revised form 30 September 2012
Accepted 2 October 2012
Available online 8 November 2012

Keywords:
Patent analysis
Network analysis
Mobile industry

A B S T R A C T

Using patent lawsuit information, we develop a method to identify companies with a significant legal influence on the technologies used in their industry. We construct a patent-infringement lawsuits graph, using the data from intellectual property lawsuits between companies, and analyse the level of influence of companies by computing the network centrality of each company in the graph. To illustrate the practicality of our method, we apply the proposed method to analyse the patent influence of well-known companies in the smartphone industry. The results of our empirical analysis are well matched to the current smartphone market status — for example, Apple, Nokia and Samsung are identified as the most important companies, which lead the smartphone technology and market. This shows that the proposed approach can be used to evaluate and manage patent portfolios even using a relatively small amount of patent lawsuits data.

1. Introduction

With the introduction of Apple's iPhone and its rivals including Google's Android, the mobile phone industry has emerged as an exciting and fast-changing field. Unlike previous smartphones, the latest smartphones, including the iPhone, enable an intuitive and rich user experiences; they are attractive to a wide range of users, not only tech-savvy but also casual users. As a result, the market for smartphones has started to grow dramatically. Nowadays more than 1.3 billion mobile phone handsets are sold annually, and smartphones made up almost 20% of that total in 2010. Sales of smartphones are doubling every year, and the total global sales volume is expected to surpass that of PCs by 2012 [1].

The explosion of the smartphone market has triggered strong competition among mobile phone manufacturers. For such companies, a common strategy is often to sue their competitors as this can damage competitors' credit or extract licence revenue out of the accused infringers. There are currently more than 50 patent-infringement lawsuits relating to smartphone technology. In October 2009, Nokia sued Apple for patent-infringement and twenty months later Apple agreed to pay Nokia patent licence fees. In addition, Apple sued HTC in March 2010 and then HTC counter sued Apple in May 2011, and Samsung and Apple also sued each other for patent-infringement around the world. In short, it appears that a sued company will try to defend its patent rights through a counterclaim. This is nothing new; the military strategist Carl von Clausewitz said ‘the best defense is a good offense’ [2]. This study is partly motivated by these recent patent-infringement cases.

This paper explores the usefulness of patent-infringement lawsuits as a measure of the *valuation* of a firm's patents. Since patents are assets to companies and considered as an evaluation factor for the value of firms, many prior research studies have been focused on evaluating the quantity and quality of patents that a company is holding to provide various information such as patent portfolio and valuation of the company to the market. However, because of security reasons, the existing studies using patents themselves often limit to access the data associated with patents and, therefore, are not practical in many cases.

* Corresponding author. Tel.: +49 6221 4342 258.
E-mail addresses: hyoung@skku.edu (H. Kim), jaeseung.song@neclab.eu (J. Song).

0040-1625/$ – see front matter © 2012 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.techfore.2012.10.014

On the other hand, information of patent-infringement lawsuits is easy to access and reflects the importance of patents well even with a small number of cases. Thus we propose a methodology that collects data from intellectual-property lawsuits in order to identify relationships between companies within the same industry and then to automate the extraction of useful characteristics of the companies from the relationships. The method can identify the roles or the relative positions of companies in the patent landscape of an industry such as the mobile phone industry. We make the following two contributions, inspired by recent advances in complex network analysis:

1. We propose a method to analyse the patent-infringement lawsuits between companies within the same industry. We construct a patent-infringement lawsuits graph from the collected patent-infringement cases, and analyse the topological positions of the companies. The most important and practical application is to measure the influence of each company in the patent-infringement lawsuits. Unlike the existing solutions [3–7] focusing on patent citation information, the proposed method uses the patent-infringement lawsuits. In many cases, the proposed method can have a key advantage over the citation patent analysis since it requires only the small number of patent litigation cases rather than tracing all the relationships between citing and cited patents which eventually lead to a citation network consisting of a large number of nodes and edges. We particularly suggest the use of the two network centrality measures (degree and eigenvector centrality) to measure each company's topological importance in the constructed patent-infringement lawsuits graph. The computed network centrality measures can be used as guidelines or reference points to help identify the roles of companies by categorising companies into four groups (see Section 2).
2. In order to show the feasibility of our method, we apply the method to analyse the recent patent-infringement lawsuits between companies in the mobile phone industry. We collect the patent-infringement cases from January 2006 to August 2011 involving 26 well-known companies in the mobile phone industry, and quantitatively measure the relative importance of each company in the patent-infringement lawsuits. According to the analysis, Apple, Nokia and Samsung can be classified as companies leading the smartphone market with their high value patents while HTC, LG, Motorola, RIM and Sony Ericsson are considered as companies that have relatively weak patent portfolios, therefore often been sued by other companies. In addition, Gemalto, InterDigital, Kodak, Microsoft, Mosaid, Qualcomm and Smartphone Technologies LLC are classified as companies that tend to sue other competitors for patent-infringement without serious threats of patent “counter-suits” by others.

The rest of the paper is organised as follows: In Section 2, we discuss some related work on patent analysis. In Section 3, we describe how to construct patent-infringement lawsuits graph from the patent-infringement cases, and the constructed graph is analysed. In Section 4, we apply the proposed method to analyse the recent patent-infringement lawsuits between representative manufacturers in the mobile phone industry. In Section 5, we discuss potential applications of the proposed method. Finally, the paper finishes with conclusions by summarising the contributions of this work and future directions in Section 6.

2. Related work

Patent analysis is in widespread use today due to the proliferation of patent related databases. The aim of this analysis is to use patent data (e.g., number of patents, application year, registration country and citation information) to derive information about a particular industry or technology used in forecasting. Because of this, patent analysis has been shown to be valuable in planning technology development. For example, [8] used patents for trend analysis by applying text-mining and data-mining techniques; [9] additionally applied network analysis to focus on conducting the analysis of patent claims; [10] used patent analysis techniques to forecast emerging technologies; [11] provided a patent-based cross impact analysis method to estimate technological impacts quantitatively; [12] identified clusters of patents by analysing similar content/structure and [13] evaluated the risk of patent infringement. Recently, [14] proposed an empirical method that relates companies' market return to information about patent citation patterns to infer innovation market competition. A study about the mobile phone industry by [15] is more highly related to our research interest than others. They illustrated how several mobile telecommunications firms (Sony-Ericsson, Nokia and Samsung) pursued patent strategies to catch up with the market leader (Motorola) through intensive analysis of the patents of the four mobile manufactures.

In order to measure technological performance, inventive performance, and/or innovative performance several patent-based indicators have been introduced. The most widely used indicator is to simply count the number of raw patents. Although raw patent counts are subject to the criticism that this naive indicator does not take into account the relatively different weights of patents [16,17], this indicator is generally accepted as one of the most appropriate indicators to evaluate the inventive or innovative performance of companies in terms of a particular technology and industry [18–23]. A more sophisticated indicator is to use patent citations [24–26]. Compared to raw counts of patents, which evaluate a purely quantitative measure, patent citations can be used to measure the qualities of patents. The basic assumption is that the number of patent citations for a particular patent indicates its importance or impact, and therefore the use of patent citations also has limitations [27]. Particularly [28] found the problem called “home bias effect” in patent citations. However, at the macroscopic level, the use of patent citations can be enough to measure the importance of patents. Recently, [29] proposed a stochastic approach to assess future technological impacts of patents over time. [30–33] have shown the validity of patent citations as an indicator of the quality of inventions or innovations by analysing the correlation between the importance of patents (evaluated by experts) and the number of citations.

One alternative approach to focus on the relationships between patents is citation networks. A citation network consists of a set of nodes representing patents and a set of edges, where an edge from node x to node y represents a citation from patent x to patent y. The citation graph can be used to evaluate authors and patents. For this purpose, the PageRank algorithm proposed by [3] is commonly used to rank the nodes in citation networks [4] because a citation network is defined as a directed graph. Also, citation networks have been studied extensively to analyse uncovering patterns, motivation, and structure of scientific collaboration. For example, [5] showed that the network density of companies within the MPEG patent pool, comprising all patents relating to this audio/video standard, was higher than those of the surrounding areas. Also, [6] empirically used citation networks in order to classify patents automatically. More recently, [7] showed that Apple has the world's leading patent portfolio in the field of smartphone technology, slightly ahead of Microsoft and IBM through the analysis of citation networks of patents likely involved in making smartphones. Our work is an extension and modification of these approaches, focusing on the patent-infringement lawsuits between companies instead of the relationships between citing and cited patents. In other words, our work mainly aims to analyse the influence of companies in patent-infringement cases while prior works have tried to measure the quality of patents by using their citations.

3. Constructing patent-infringement lawsuits graphs

In this section we present an analysis based on network theory with patent-infringement lawsuits between companies. Recent advances in the social network analysis have provided us with the mathematical and computational tools to understand many important phenomena depending on networks, from human relationships through social interactions between people to explicit networks such as the Internet and mobile sensor network better [34,35]. Often the topology of a network has distinctive features, such as vertex order distribution, clustering and characteristic path lengths, which can be explained in terms of its evolution and which in turn explain some aspects of its behaviour. For example, the most recognizable airport hubs (e.g., Chicago, Frankfurt and Beijing) in the world can be identified through a network analysis of the structure of the worldwide air transportation network [36].

We construct a directed graph called a patent-infringement lawsuits graph with the collected patent-infringement lawsuits. A lawsuits graph consists of a set of nodes representing companies and a set of edges, where an edge from node x to node y represents the lawsuit relationship from x to y; that is, the edge (x,y) is added when the company x has sued the company y. For an example, suppose that we have three companies $V=\{x,y,z\}$. When they are involved in the following patent-infringement cases: $E=\{y\rightarrow x, y\rightarrow z, z\rightarrow y\}$, we can construct the lawsuits graph $G=(V,E)$ as shown in Fig. 1.

We use the generated graph to analyse the patent-infringement lawsuit relationships. From the constructed graph, we can identify active patent holders, patent trolls, main target companies, and/or key players in the patent landscape by computing the network centrality of each company in this graph. We will discuss how to analyse the constructed patent-infringement lawsuits graphs in the next sections.

3.1. Network centrality

A node's network centrality illustrates its relative importance in the network. In this section, we introduce the four network centrality measures (degree, closeness, betweenness and eigenvector centrality [37]) that are widely used in network analysis and explain their implication in patent-infringement lawsuits graphs.

Degree centrality simply measures the number of direct connections to other nodes. Since a patent-infringement lawsuits graph is a directed graph, we need to consider both in- and out-degrees of a node. We define that the out-degree of a node u is the number of nodes it is linked to, and the in-degree of u is the number of edges incoming to the node. These are calculated for a node u as the ratio of the number of incoming edges of node u for in-degree centrality (or outgoing edges for out-degree centrality) to the total number of all other nodes in the network:

$$C_{\deg}(u)=\frac{\deg(u)}{|V|-1} \qquad (1)$$

where $\deg(u)$ is the number of node u's incoming edges for in-degree centrality (or outgoing edges for out-degree centrality).

In patent-infringement lawsuits graphs, out-degree centrality indicates how many companies the company u has sued. This centrality measure reflects a company u's direct patent influence on the other companies. On the other hand, in-degree centrality indicates how many companies have sued the company u. This centrality measure explains the level of patent-infringement lawsuits targeted by the other companies. However, degree centrality does not take into account the topological positions of

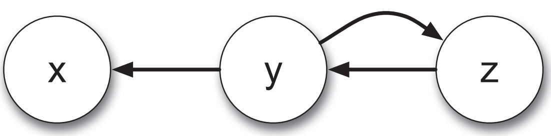

Fig. 1. An example of patent-infringement lawsuits graph. Given the patent-infringement lawsuits $E=\{y\rightarrow x, y\rightarrow z, z\rightarrow y\}$ between three companies $V=\{x,y,z\}$, we construct the patent-infringement lawsuits graph $G=(V,E)$.

nodes. Although nodes may be locally well connected to their immediate neighbours, they can be part of a relatively isolated clique.

Closeness centrality expands the definition of degree centrality by measuring how close a node is to all the other nodes. In patent-infringement lawsuits graphs, if we assume that patent-infringement lawsuits are *transitive*, the closeness of a node might signify how much influence it have on other linked nodes. If, for example, a node has high closeness centrality, it actively sues other companies and provides high influence on patent infringement disputes. This is calculated for a node u as the average inverse shortest path length to all other nodes in the network:

$$C_{clo}(u) = \frac{\left[\sum_{v \neq u \in V} \mathrm{dist}(u, v)\right]^{-1}}{|V|-1} \tag{2}$$

where dist(u,v) is the length of the shortest path from node u to node v.

Betweenness centrality measures the paths that pass through a node and can be considered as the proportional flow of data through each node. In patent-infringement lawsuits graphs, if we assume that patent-infringement lawsuits are transitive, betweenness centrality might signify the ability to isolate, influence, manipulate or prevent patent-infringement lawsuits between other companies. Therefore, those companies on shortest paths between other companies are playing key roles of activating patent infringement disputes for technologies and will be a key player on the patent-infringement lawsuits relationship [38]. Nodes that are often on the shortest-path between other nodes are deemed highly central because they control the flow of information in the network. This centrality is calculated for a node u as the proportional number of shortest paths between all node pairs in the network that pass through u:

$$C_{bet}(u) = \frac{1}{(|V|-1)\cdot(|V|-2)} \sum_{s \neq u, t \neq u \in V} \frac{\sigma_{s,t}(u)}{\sigma_{s,t}} \tag{3}$$

where $\sigma_{s,t}$ is the total number of shortest paths from source node s to destination node t, and $\sigma_{s,t}(u)$ is the number of shortest paths from source node s to destination node t which actually pass through node u.

In Fig. 2, for example, the nodes N_d, N_c and N_b illustrate the characteristics of these network centrality measures. These nodes have the highest degree, closeness and betweenness centrality measures, respectively. We note that closeness and betweenness centrality measures might not be suited for large-scale graphs due to their high computational complexity of $O(nm)$ time where n and m are the numbers of nodes and edges, respectively [39].

Eigenvector centrality [40] is a more sophisticated version of the degree centrality. Whereas degree centrality gives a simple count of the number of connections a node has, eigenvector centrality does not assume that all connections are equal and is the centrality measure that has to do with indirect influence. Therefore, this centrality can be used properly to analyse the influence of a patent lawsuit. Eigenvector centrality is defined as the principal eigenvector of the adjacency matrix defining the network. The key idea of this centrality measure is that the prominence of a node u is understood to be proportional to the combined prominence of its neighbours. This is calculated for a node u as follows:

$$C_{eig}(u) = \frac{1}{\lambda} \sum_{v \in N(u)} W_{u,v} \cdot C_{eig}(v) \tag{4}$$

where $N(u)$ is the set of nodes reachable directly from u and λ is a constant. With vector–matrix notation, this equation can be rewritten as $\lambda \cdot C_{eig} = W \cdot C_{eig}$ where $C_{eig} = \left(C_{eig}(v)\right)_{v \in V}$ and $W = \left(W_{u,v}\right)_{u,v \in V}$. Therefore C_{eig} is an eigenvector of the weighted adjacency matrix W with eigenvalue λ.

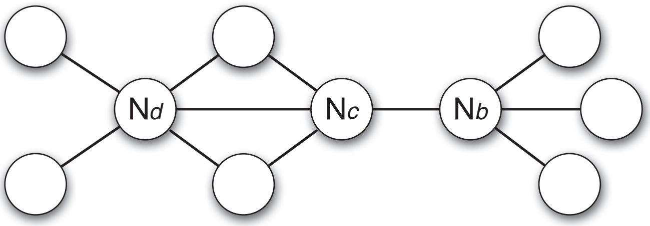

Fig. 2. The characteristics of network centrality. In this network, N_d has higher degree centrality than N_c since N_d has five neighbours while N_c has higher closeness centrality than N_d. We note that N_d is located at the periphery of the network compared to N_c. Interestingly, N_b has the highest betweenness centrality. We can see that N_b plays a 'bridge' role for the rightmost nodes.

In patent-infringement lawsuits graphs, eigenvector centrality measures the combined prominence of the companies that *u* has sued. With this centrality, we can consider a company *u*'s influence based on which companies are being sued for infringement on patent held by the company *u*. If the influence of the sued companies is large, the influence of the company *u* is also large. For example, even if a company sues just one other company, which subsequently sues many other companies, then the first company in that patent chain can be considered highly influential.

3.2. Identifying roles of companies

We can identify the roles of companies using their network centrality in patent-infringement lawsuits graphs. We suggest that a node's network centrality shows its specific characteristic in patent infringement suits between companies. In order to do this quantitatively, we categorise network centrality into four types and introduce two patent centrality levels that help us to understand companies' characteristics.

First of all, the centrality measures, such as out-degree, closeness, betweenness and eigenvector introduced in Section 1, can be used for measuring the activity of patent rights protection. The higher centrality addresses more active associations with others in a network. For example, in a social network, a person with the higher centrality often has the more power in terms of organisational behaviour [41]. Therefore, our research also uses these centrality measures in order to understand importance and influence of patent infringement lawsuits. In other words, the companies with a high activeness level are regarded as the active patent holders who frequently assert their rights to exclude infringing rivals or to make money by forcing other companies to pay licencing fees.

In direct opposition to the above network centrality type, in-degree centrality can be used for measuring the number of conflicts involved in defending patent-infringement lawsuits.

In other words, companies with a high passiveness level are regarded as the main target companies against patents holders. We will discuss this characteristic through the case study in Section 4.

Fig. 3 summarises the companies' specific roles with the patent levels and individual companies in a patent-infringement lawsuits graph can be characterised by the patent activeness/passiveness level as follows:

1. Group 1 (key player): In the patent-infringement lawsuits, companies in this group not only assert their patent rights to exclude infringing rivals and/or to protect their exclusive and profitable technologies but also are often sued by other companies for patent-infringement lawsuits [42]. Therefore, the companies have high level of activeness and passiveness. This is mainly because they hold high number of patents and achieve high business profits than other companies in the same industry.
2. Group 2 (patent troll): The individuals or companies which own their patent rights for the sole purpose of collecting licencing fees (high activeness level) and damage awards from patent-infringement lawsuits rather than the protection of their technologies (low passiveness level) are categorised in this group. In general, companies having characteristics of this group do not intend to manufacture products based on their patents and often are called as “patent troll” [43]. They wait for other companies to increase business profits by utilising their patented technology and then enforce their patents on the alleged infringers.
3. Group 3 (victim): The companies in this group are often sued by companies in Group 1 and/or Group 2 for patent-infringement and thereby have high activeness level. However, this group generally does not countersue since companies in Group 3 do not hold the proper patent claims against the suing companies (low activeness level). Usually medium-scale companies fit into this category. Group 1 companies use patent-lawsuits to exclude Group 3 companies from the market, while Group 2 companies sue for the purpose of obtaining money.

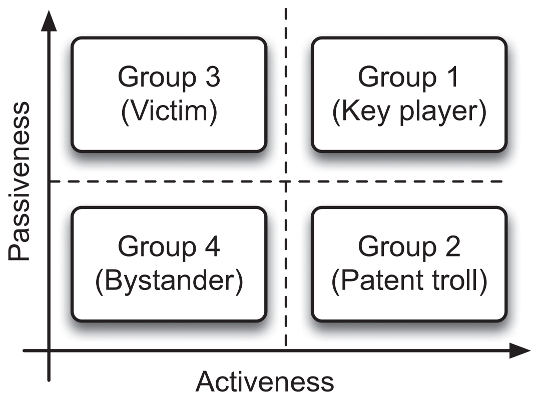

Fig. 3. Roles of companies according to their patent activeness and patent passiveness.

4. Group 4 (bystander): There are companies that usually avoid to be involved in patent-infringement lawsuits or do not actively sue other companies. They have low level of activeness and passiveness. Firms that start to enter new markets can be fit into this group because they do not have enough patents to sue other companies and their business profits are not high enough to be targeted by companies in Group 1 or Group 2.

4. The case study of the smartphone patent-infringement lawsuits

We demonstrate the practicality of our method by analysing the recent patent-infringement lawsuits between companies in the mobile phone industry. For this purpose, we use a sample set of 26 well-known companies: Apple, AT&T, Barnes&Noble, Foxconn, Gemalto, Google, HTC, Huawei, InterDigital, Inventec, Kodak, Kyocera, LG, Microsoft, Mosaid, Motorola, Nokia, NTP, Oracle, Qualcomm, RIM, Samsung, Sanyo, Sony Ericsson, Smartphone Technologies LLC and ZTE. We collect the datasets of the lawsuits from January 2006 to August 2011 between these companies, which resulted in the intensive searches for several combinations of company names and specific words such as 'sue', 'patent', 'lawsuit' and 'settlement' involved in patent-infringement lawsuits. Appendix A shows the brief description of the collected datasets (see patent-infringement lawsuits and licence settlement cases). For example, we searched the Google News[1] using the combinations of keywords ('Apple', 'Samsung', 'patent' and 'sue') to find the news stories of patent infringement cases from January 2006 to August 2011 between Apple and Samsung. From these news stories, we manually filtered only the unique patent infringement cases. We repeated this process by changing the keywords (e.g. using 'lawsuit' instead of 'sue') until there is no new case in the search results.

Using the method described in Section 3, from the collected datasets, we construct the directed graph named a 'patent-infringement lawsuits graph'. The resulting graph is shown in Fig. 4.

In order to analyse the *patent activeness level* of each node, first we compute out-degree and eigenvector centrality measures. The results are shown in Table 1. For the computation of eigenvector centrality, the eigenvectors and eigenvalues of the weighted adjacency matrix W are calculated using the 'NumPy'[2] module of the Python programme. In Table 1, we can identify the companies with a high centrality value which is greater than the average value, for out-degree and eigenvector centrality measures. Each time Apple, Gemalto, Kodak, Microsoft, Motorola and Smartphone Technologies LLC (STL) are classified as these companies. InterDigital, Mosaid, Nokia, Qualcomm, Samsung and Sony Ericsson (Sony) also reached similar positions once.

We also identify the companies that are most frequently sued by other companies for patent-infringement lawsuits with the *patent passiveness level* of each node, which can be analysed by computing the in-degree centrality. This result is shown in Table 1 (the third column). Apple, Google, HTC, Huawei, LG, Motorola, Nokia, RIM, Samsung, Sony and ZTE always are identified as the companies with a high centrality which is greater than or equal to the average centrality for in-degree.

As discussed in Section 2, we can classify the role of each company into one of the four classes with the activeness and passiveness levels of companies. For this categorisation, we used the k-means algorithm [44] where $k = 4$, which is a method commonly used to automatically partition n observations into k groups in which each observation belongs to the cluster with the nearest mean (called "centroid"). For k-means algorithm, we fixed a maximum of 1000 iterations, which are safe enough to guarantee the algorithm converge to optimal solutions.

Unlike other social networks, the concept of a shortest path between any two nodes is not clearly established in patent-infringement lawsuits graphs since we cannot assume that z is influenced by x in an indirect manner when the company x has sued the company y and the company y has sued the company z, respectively, for patent-infringement. In order to check if there exists a transitivity in the generated graph in Fig. 4, we compute the transitivity by measuring the number of transitive triangles in the graph (i.e., if node x is directly connected to node y and node y is directly connected to node z, node x is directly connected to node z) [45]. Interestingly, the computed transitivity (0.098) is less than the average transitivity (0.154) of 1000 random graphs with the same numbers of nodes and edges. Hence, in this case study, we only use three centrality measures, i.e., in-degree, out-degree and eigenvector, for categorisation.

With these three centrality measures, we tested the feasibilities of several distance metrics [46] such as the Pearson correlation, the Euclidean, and the city-block distance and then found that the city-block distance metric performs well — in order to minimize the relative contribution of each centrality metric to the distance, we also normalized all company's centrality values by dividing the values for each centrality metric by the range (i.e., maximum–minimum) of that centrality.

The clustering results are shown in Fig. 5. This figure shows the four clusters of companies that are identified by the k-means clustering algorithm with the calculated centrality values when $k = 4$. The symbol '+' represents the centroid which is the mean of the points in each cluster. Using relative positions of centroids of clusters, we can label the four clusters as the four groups (red-circle: Group 1 (key player), cyan-diamond: Group 2 (patent troll), blue-triangle: Group 3 (victim) and green-rectangle: Group 4 (bystander)) of companies. Table 2 shows the names of the classified companies.

[1] http://news.google.com/
[2] http://numpy.scipy.org/

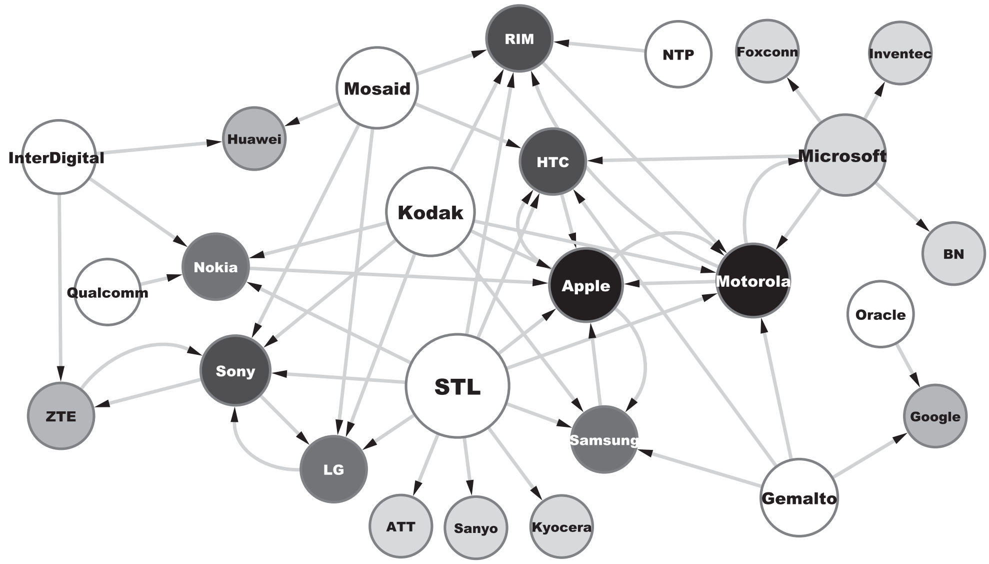

Fig. 4. The patent-infringement lawsuits graph for 26 well-known companies in the mobile phone industry in January 2006–August 2011. In this graph, a node represents a company and an edge from node *x* to node *y* represents the lawsuit relationships from *x* to *y*. For more effective visual representation, the size of each node is increased to be linearly proportional to the node's out-degree and the colour interval between white and black is used to render the node's in-degree centrality. The higher the node's in-degree value is, the darker the node is. In this graph, Apple and Motorola have the highest in-degree centrality while Smartphone Technologies LLC has the highest out-degree centrality.

We found that the three (Apple, Nokia and Samsung) and the seven companies (Gemalto, InterDigital, Kodak, Microsoft, Mosaid, Qualcomm, Smartphone Technologies LLC) are positioned in Group 1 and Group 2, respectively, in the collected patent-infringement lawsuits. We compared the companies in Group 1 with the companies ranked 1 to 3 by sales in 2012

Table 1
Companies ranked according to patent activeness/passiveness levels in descending order. We use a bold font to identify the companies with a high centrality which is greater than or equal to the average centrality for each centrality measure, respectively. The average centrality of each centrality is 0.080 (out-degree), 0.109 (eigenvector) and 0.080 (in-degree).

Out-degree		Eigenvector		In-degree	
Name	Value	Name	Value	Name	Value
STL	**0.440**	**Kodak**	**0.710**	**Apple**	**0.240**
Kodak	**0.280**	**Apple**	**0.321**	**Motorola**	**0.240**
Microsoft	**0.200**	**Nokia**	**0.290**	**HTC**	**0.200**
Mosaid	**0.200**	**Samsung**	**0.290**	**RIM**	**0.200**
Gemalto	**0.160**	**STL**	**0.269**	**Sony**	**0.200**
Apple	**0.120**	**Qualcomm**	**0.262**	**LG**	**0.160**
InterDigital	**0.120**	**Microsoft**	**0.158**	**Samsung**	**0.160**
Motorola	**0.120**	**HTC**	**0.145**	**Nokia**	**0.160**
Sony	**0.080**	**Gemalto**	**0.125**	**Google**	**0.080**
HTC	0.040	**Motorola**	**0.120**	**Huawei**	**0.080**
LG	0.040	InterDigital	0.065	**ZTE**	**0.080**
Nokia	0.040	Mosaid	0.039	AT&T	0.040
NTP	0.040	RIM	0.027	B&N	0.040
Oracle	0.040	NTP	0.024	Foxconn	0.040
Qualcomm	0.040	AT&T	0.000	Inventec	0.040
RIM	0.040	B&N	0.000	Kyocera	0.040
Samsung	0.040	Foxconn	0.000	Microsoft	0.040
ZTE	0.040	Google	0.000	Sanyo	0.040
AT&T	0.000	Huawei	0.000	Gemalto	0.000
B&N	0.000	Inventec	0.000	InterDigital	0.000
Foxconn	0.000	Kyocera	0.000	Kodak	0.000
Google	0.000	LG	0.000	Mosaid	0.000
Huawei	0.000	Oracle	0.000	NTP	0.000
Inventec	0.000	Sanyo	0.000	Oracle	0.000
Kyocera	0.000	Sony	0.000	Qualcomm	0.000
Sanyo	0.000	ZTE	0.000	STL	0.000

Abbreviation: B&N, Barnes&Noble; Sony, Sony Ericsson; STL, Smartphone Technologies LLC.

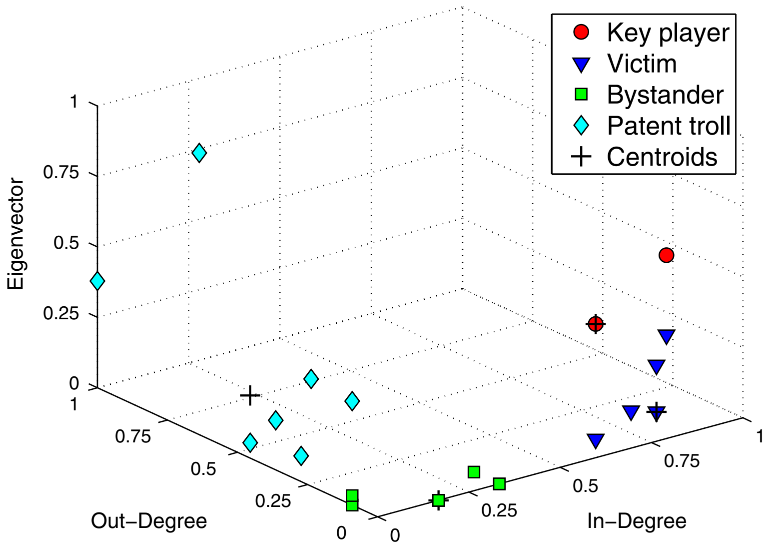

Fig. 5. Three-dimensional scatter plot graph showing the four groups (red-circle: Group 1 (key player), cyan-diamond: Group 2 (patent troll), blue-triangle: Group 3 (victim) and green-rectangle: Group 4 (bystander)) of companies that identified by the *k*-means clustering algorithm with the calculated centrality values when $k=4$. *X*-axis, *Y*-axis and *Z*-axis represent the in-degree, out-degree and eigenvector centrality values of the companies, respectively. Each centroid (+) is the mean of the points in each cluster. We labelled the four clusters by examining relative positions of centroids of clusters.

(1:Samsung, 2:Apple and 3:Nokia) and found that the lists are identical [47]. We also found that most companies considered as patent trolls (InterDigital, Mosaid, NTP, Qualcomm and SmartPhone Technologies LLC) on the ongoing patent disputes in the field of smartphone technologies also appeared in the list of Group 2. We can also see that Kodak and Microsoft might play the role of patent troll in practice rather than manufactures. HTC, LG, Motorola, RIM and Sony Ericsson play relatively passive roles in the patent disputes compared with their rivals (Apple, Nokia and Samsung) [1].

We should be cautious in discussing the quality of patents held by the companies used in the case study since the scope of the claims in some patent-infringement cases is vague, and many of the claims will eventually be concluded as invalid in practice. Our analysis is not designed to explicitly measure the quality of patents held by companies. Instead we focus on the influence of companies in patent-infringement lawsuits.

5. Discussion

Our approach has the potential to measure and visualise the patent activeness and patent passiveness levels of companies using the proposed network analysis. Also, the approach can analyse the temporal trends of patent-infringement lawsuits between companies by iterating the analysis over time. The following two points show how to achieve these.

First, the analysis of patent-infringement lawsuits graph shows the relative position of each company in a technology market. This result can be used to evaluate and manage companies' patent portfolios. As an illustration, we identified Google as Group 4 (see Table 2). In practice Google acquired Motorola Mobility having reasonable patent activeness levels (out-degree: 0.120 and eigenvector: 0.120) compared with the average centrality values (out-degree: 0.080 and eigenvector: 0.109) and its patents for about $12.5 billion in order to strengthen patent portfolio, which will protect Android from anti-competitive threats. This deal shows that our analysis is practically useful to explore the influence of patents between companies. For the same reason, the recent patent disputes in the smartphone industry (see Table 3) showed that the companies identified as Group 1 (key player) in Section 4 are highly involved in the latest disputes. This implies that the identification of Group 1 companies is highly accurate. In order to confirm the validity of our analysis, we compare the companies (Apple, Gemalto, HTC,

Table 2
Classification of companies according to their topological roles in the patent-infringement lawsuits graph generated for 26 well-known companies in the mobile phone industry.

Role	Company
Group 1 (*Key player*)	Apple, Nokia, Samsung
Group 2 (*Patent troll*)	Gemalto, InterDigital, Kodak, Microsoft, Mosaid, Qualcomm, Smartphone Technologies LLC
Group 3 (*Victim*)	HTC, LG, Motorola, RIM, Sony Ericsson
Group 4 (*Bystander*)	AT&T, Barnes&Noble, Foxconn, Google, Huawei, Inventec, Kyocera, NTP, Oracle, Sanyo, ZTE

Table 3
Four representative recent news on patent in smartphone industry.

Date	Disputes	Description
Sep.2011	*Samsung* vs. *Apple*	Apple won the latest dispute with Samsung as a court in the Hague banned three Samsung telephone models, ruling that the company has infringed an Apple photo management patent.
Aug.2011	*Google purchased Motorola*	Google acquired Motorola Mobility and its patent portfolio for about $12.5 billion in order to protect Android from anti-competitive threats.
Jul.2011	*HTC* vs. *Apple*	Apple has won a preliminary ruling from a US trade panel judge that HTC infringed on two of Apple's patents.
Jun.2011	*Apple* vs. *Nokia*	After two-year fight with Apple over smartphone technology, Nokia could receive a one-off payment of more than 800 m euro and further royalties in the future.

InterDigital, Kodak, Microsoft, Mosaid, Motorola, Nokia, Qualcomm, Samsung, Smartphone Technologies LLC, and Sony Ericsson) having a high patent activeness level in our analysis with the leading patent owner companies (Apple, IBM, InterDigital, Microsoft, Motorola, Nokia, Qualcomm, RIM, Sony Ericsson and Sun Microsystems) which were identified by analysing the citation network between patents in [7]. From this comparison, we can see that many companies (Apple, InterDigital, Microsoft, Motorola, Nokia, Qualcomm and Sony Ericsson) are commonly included in both lists. This shows that our analysis is reasonable. Moreover, our approach has a key advantage over the citation patent analysis; it requires only the patent litigation cases rather than tracing the relationships between citing and cited patents which eventually leads to a citation network consisting of a large number of nodes and edges.

Second, patent-infringement lawsuits graphs can be used to help a company analyse and manage its patent portfolio. In Section 4, our case study considers all types of patents over smartphone technologies including software, hardware, communications, design and etc. Therefore, the constructed graph represents the overall snapshot to show the patent relationships between companies within the smartphone industry. In the next step, we are able to perform the patents lawsuits analysis with a finer granularity. In other words, the generated lawsuits graph can be further subdivided into several lawsuits graphs according to sub-technologies. For example, if we subdivide a smartphone technology into several sub-categories such as communication and software, an independent lawsuits graph for each sub-technology can be generated, respectively. From these graphs, we can identify the weak and strong points of each company for a given technology by analysing companies' topological positions in each graph, and hence suggest where we need to invest more, to balance growing technologies.

Third, patent analysis results derived from patent-infringement lawsuits graphs can also be advantageous to patent attorneys. Since patent attorneys play many roles, such as increasing profits from legal protection for given inventions of a company and protecting inventions from infringements as well as participating in patent licence negotiations, they can use the proposed method differently based on their clients. For example, attorneys for firms that have good patent portfolios (i.e., companies in Group 1 or 2) can list up potential target companies for patent prosecutions using analysis results. On the other hand, attorneys of companies in Groups 3 or 4 can use analysis results on establishing a strategy for patent licencing. If their companies are sued from Group 2 (patent troll) companies such as Microsoft, they can guide the companies to perform patent licence negotiations instead of patent disputes; otherwise, they might plan to counter-sue the companies that have sued their customers. In addition, the analysis results can also be used for the attorneys to find new potential clients.

6. Conclusion

This article introduced the usefulness of patent-infringement lawsuits between companies and aimed at evaluating the companies' patents which can affect the valuation of the companies. We proposed how to construct a graph from patent litigation cases over some time frame and then analyse the influence of companies by computing network centrality in the constructed graph. The calculated network centrality measures, which show the activeness (out-degree and eigenvector centrality measures) and passiveness (in-degree centrality) levels of companies in patent disputes, can be used to identify their roles or characteristics. The proposed approach is relatively efficient compared to the conventional patent analysis methods [3–7], which focus on patent citation, since our method uses only patent-infringement lawsuits instead of the whole companies' patents and their citations. As a case study, we analysed the recent patent litigation cases between 26 representative companies in the mobile phone industry from January 2006 to August 2011. Our analysis results are well matched to the current smartphone market status. Apple, Nokia and Samsung are classified as the most important companies, which lead the smartphone technology and market, in the ongoing patent wars.

Our approach can be used to evaluate and manage patent portfolios by measuring the relative importance of each company for the patent-infringement lawsuits. We do not claim that our method is a full replacement for commonly used conventional company evaluation methods, but a useful complementary method for the evaluation of companies' patent portfolios. For example, we can effectively visualise how the influence of a company changes over time with the changes in its centrality.

Having relied on a relatively small sample pool (65 cases between 26 companies), there are some limitations in generalising our observations about the usefulness of the proposed method. First, the behaviours of patent infringement litigation can be varied depending on the target domain. Next, since we used an unweighted graph to avoid biassed weights, the relative importance of patent lawsuits is not captured properly. Additionally, it is difficult to model a weighted graph for patent infringement lawsuits given the many factors such as the claims per lawsuit and the quality of patents. We also plan to develop a predictive analysis of patent influence between companies under a probabilistic model (e.g., [48]) by estimating the realistic probabilities for settlements of patent-infringement lawsuits.

Appendix A. Patent-infringement lawsuits and licence settlement datasets

Table A.4 shows patent-infringement lawsuits and licence settlements between representative companies in the mobile phone industry from January 2006 to August 2011. In each relationship, the left company represents a patent owner while the right company represents a dependent or licensee company. For each n(country) in 'Status', n and `country` represent the number of patents involved in a lawsuit and the country filed the lawsuit, respectively (the symbol '?' represents unknown cases). The status of `resolved` indicates that the case was settled.

Table A.4
Patent-infringement lawsuits and licence settlements between representative companies in the mobile phone industry from January 2006 to August 2011.

No.	Patent relationship	Date	Status
1	Kodak → Motorola	Jan. 2006	resolved
2	NTP → RIM	Mar. 2006	resolved
3	Kodak → Sony	Jan. 2007	resolved
4	Motorola → RIM	Feb. 2008	7(US)
5	RIM → Motorola	Fen. 2008	1(US)
6	Qual → Nokia	Jul. 2008	resolved
7	Kodak → Nokia	Oct. 2008	resolved
8	Kodak → LG	Dec. 2009	resolved
9	Kodak → Samsung	Jan. 2010	resolved
10	Motorola → RIM	Jan. 2010	5(US)
11	Apple → HTC	Mar. 2010	20(US)
12	STL → Apple	Mar. 2010	6(US)
13	STL → AT&T	Mar. 2010	6(US)
14	STL → LG	Mar. 2010	6(US)
15	STL → Motorola	Mar. 2010	6(US)
16	STL → RIM	Mar. 2010	6(US)
17	STL → Samsung	Mar. 2010	6(US)
18	STL → Sanyo	Mar. 2010	6(US)
19	HTC → Apple	May 2010	5(US)
20	Apple → HTC	Jun. 2010	4(US)
21	Oracle → Google	Aug. 2010	7(US)
22	Apple → Motorola	Oct. 2010	2(US)
23	Gemalto → Google	Oct. 2010	1(US)
24	Gemalto → HTC	Oct. 2010	1(US)
25	Gemalto → Motorola	Oct. 2010	1(US)
26	Gemalto → Samsung	Oct. 2010	1(US)
27	MS → Motorola	Oct. 2010	9(US)
28	Motorola → Apple	Oct. 2010	18(US)
29	Motorola → MS	Oct. 2010	16(US)
30	STL → HTC	Oct. 2010	8(US)
31	STL → Kyocera	Oct. 2010	8(US)
32	STL → Nokia	Oct. 2010	8(US)
33	STL → Sony	Oct. 2010	8(US)
34	Kodak → Apple	Jan. 2011	1(US)
35	Kodak → RIM	Jan. 2011	1(US)
36	MS → BN	Mar. 2011	6(US)
37	MS → Foxconn	Mar. 2011	6(US)
38	MS → Inventec	Mar. 2011	6(US)
39	Mosaid → Huawei	Mar. 2011	6(US)
40	Mosaid → LG	Mar. 2011	resolved
41	Mosaid → RIM	Mar. 2011	6(US)
42	Apple → Samsung	Apr. 2011	7(US)
43	Samsung → Apple	Apr. 2011	3(GE)
44	Samsung → Apple	Apr. 2011	2(Japan)
45	Samsung → Apple	Apr. 2011	5(Korea)
46	Sony → ZTE	Apr. 2011	3(UK)
47	Sony → ZTE	Apr. 2011	3(Italy)
48	Sony → ZTE	Apr. 2011	3(GE)
49	ZTE → Sony	Apr. 2011	?(China)
50	MS → HTC	May 2011	resolved
51	Apple → Samsung	Jun. 2011	?(Korea)
52	Apple → Samsung	Jun. 2011	8(US)
53	Nokia → Apple	Jun. 2011	resolved
54	Samsung → Apple	Jun. 2011	?(Italy)

(continued on next page)

Table A.4 (*continued*)

No.	Patent relationship	Date	Status
55	Samsung → Apple	Jun. 2011	?(UK)
56	Samsung → Apple	Jun. 2011	5(US)
57	Apple → HTC	Jul. 2011	5(US)
58	Inter → Huawei	Jul. 2011	7(US)
59	Inter → Nokia	Jul. 2011	7(US)
60	Inter → ZTE	Jul. 2011	7(US)
61	Mosaid → HTC	Jul. 2011	3(US)
62	Mosaid → Sony	Jul. 2011	3(US)
63	HTC → Apple	Aug. 2011	3(US)
64	LG → Sony	Aug. 2011	resolved
65	Sony → LG	Aug. 2011	resolved

References

[1] M. Kenney, B. Pon, Structuring the smartphone industry, Is the Mobile Internet OS Platform the Key?, Discussion Papers 1238, The Research Institute of the Finnish Economy, 2011.
[2] H.w.G. Carl von Clausewitz, Principles of War, by Carl Von Clausewitz, Bodley Head, 1943.
[3] S. Brin, L. Page, The anatomy of a large-scale hypertextual web search engine, in: Computer Networks and ISDN Systems, Proceedings of the Seventh International World Wide Web Conference, 30, 1998, pp. 107–117.
[4] A. Sidiropoulos, Y. Manolopoulos, A new perspective to automatically rank scientific conferences using digital libraries, Inf. Process. Manage. Int. J. 41 (2005) 289–312.
[5] G. Clarkson, D. Dekorte, The problem of patent thickets in convergent technologies, Ann. N. Y. Acad. Sci. 1093 (2006) 180–200.
[6] X. Li, H. Chen, Z. Zhang, J. Li, Automatic patent classification using citation network information: an experimental study in nanotechnology, in: Proceedings of the 7th ACM/IEEE-CS joint conference on Digital libraries, JCDL'07, ACM, New York, NY, USA, 2007, pp. 419–427.
[7] Griffith Hack, Smartphone Patent Wars — Network Patent Analysis, , 2011.
[8] B.-U. Yoon, C.-B. Yoon, Y.-T. Park, On the development and application of a self-organizing feature map-based patent map, R&D Manage. 32 (2002) 291–300.
[9] J. Shin, Y. Park, Generation and application of patent claim map: text mining and network analysis, J. Intellect. Prop. Rights 10 (2005) 198–205.
[10] T.U. Daim, G. Rueda, H. Martin, P. Gerdsri, Forecasting emerging technologies: use of bibliometrics and patent analysis, Technol. Forecast. Soc. Change 73 (2006) 981–1012.
[11] C. Choi, S. Kim, Y. Park, A patent-based cross impact analysis for quantitative estimation of technological impact: the case of information and communication technology, Technol. Forecast. Soc. Change 74 (2007) 1296–1314.
[12] S.-H. Huang, H.-R. Ke, W.-P. Yang, Structure clustering for Chinese patent documents, Expert Syst. Appl. 34 (2008) 2290–2297.
[13] I. Bergmann, D. Butzke, L. Walter, J.P. Fuerste, M.G. Moehrle, V. Erdmann, Evaluating the risk of patent infringement by means of semantic patent analysis: the case of DNA chips, R&D Manage. 38 (2008) 550–562.
[14] D. Patel, M.R. Ward, Using patent citation patterns to infer innovation market competition, Res. Policy 40 (2011) 886–894.
[15] Z.-L. He, K. Lim, P.-K. Wong, Entry and competitive dynamics in the mobile telecommunications market, Res. Policy 35 (2006) 1147–1165.
[16] G. Dosi, Sources, procedures, and microeconomic effects of innovation, J. Econ. Lit. 26 (1988) 1120–1171.
[17] W.M. Cohen, R.C. Levin, in: Empirical studies of innovation and market structure, Handbook of Industrial Organization, 2, Elsevier, 1989, pp. 1059–1107.
[18] H. Aspden, Patent statistics as a measure of technological vitality, World Patent Inf. 5 (1983) 170–173.
[19] Z.J. Acs, D.B. Audretsch, Patents as a measure of innovative activity, Kyklos 42 (1989) 171–180.
[20] Z. Griliches, Patent statistics as economic indicators: a survey, J. Econ. Lit. 28 (1990) 1661–1707.
[21] G. Napolitano, G. Sirilli, The patent system and the exploitation of inventions: results of a statistical survey conducted in Italy, Technovation 10 (1990) 5–16.
[22] C. Freeman, L. Soete, The Economics of Industrial Innovation, 3rd edition The MIT Press, 1997.
[23] H. Bresman, J. Birkinshaw, R. Nobel, Knowledge transfer in international acquisitions, J. Int. Bus. Stud. 30 (1999) 439–462.
[24] M. Trajtenberg, A penny for your quotes: patent citations and the value of innovations, Rand J. Econ. 21 (1990) 172–187.
[25] A.B. Jaffe, M. Trajtenberg, R. Henderson, Geographic localization of knowledge spillovers as evidenced by patent citations, Q. J. Econ. 108 (1993) 577–598.
[26] D. Harhoff, F. Narin, F.M. Scherer, K. Vopel, Citation frequency and the value of patented inventions, Rev. Econ. Stat. 81 (1999) 511–515.
[27] D. Barberá-Tomás, F. Jiménez-Sáez, I. Castelló-Molina, Mapping the importance of the real world: the validity of connectivity analysis of patent citations networks, Res. Policy 40 (2011) 473–486.
[28] J. Michel, B. Bettels, Patent citation analysis: a closer look at the basic input data from patent search reports, Scientometrics 51 (2001) 185–201.
[29] C. Lee, Y. Cho, H. Seol, Y. Park, A stochastic patent citation analysis approach to assessing future technological impacts, Technol. Forecast. Soc. Change 79 (2011) 16–29.
[30] M.P. Carpenter, F. Narin, P. Woolf, Citation rates to technologically important patents, World Patent Inf. 3 (1981) 160–163.
[31] F. Narin, N. Elliot, P. Ross, Patents as indicators of corporate technological strength, Res. Policy 16 (1987) 143–155.
[32] M.B. Albert, D. Avery, F. Narin, P. McAllister, Direct validation of citation counts as indicators of industrially important patents, Res. Policy 20 (1991) 251–259.
[33] M.M.S. Karki, Patent citation analysis: a policy analysis tool, World Patent Inf. 19 (1997) 269–272.
[34] S. Boccaletti, V. Latora, Y. Moreno, M. Chavez, D. Hwang, Complex networks: structure and dynamics, Phys. Rep. 424 (2006) 175–308.
[35] In: M.E.J. Newman, A.L. Barabási, D.J. Watts (Eds.), The Structure and Dynamics of Networks, Princeton University Press, 2010.
[36] R. Guimerà, S. Mossa, A. Turtschi, L.A.N. Amaral, The worldwide air transportation network: anomalous centrality, community structure, and cities' global roles, Proc. Natl. Acad. Sci. 102 (2005) 7794–7799.
[37] S.P. Borgatti, Centrality and network flow, Soc. Networks 27 (2005) 55–71.
[38] C. Sternitzke, A. Bartkowski, R. Schramm, Visualizing patent statistics by means of social network analysis tools, World Patent Inf. 30 (2008) 115–131.
[39] U. Brandes, A faster algorithm for betweenness centrality, J. Math. Sociol. 25 (2001) 163–177.
[40] P. Bonacich, Factoring and weighting approaches to status scores and clique identification, J. Math. Sociol. 2 (1972) 113–120.
[41] D. Brass, M. Burkhardt, Centrality and power in organizations, in: N. Nohria, R. Eccles (Eds.), Networks and Organizations: Theory and Practice, 1993, pp. 191–215.
[42] S. Powell, Accounting for intangible assets: current requirements, key players and future directions, Eur. Account. Rev. 12 (2003) 797–811.
[43] J.F. McDonough, The myth of the patent troll: an alternative view of the function of patent dealers in an idea economy, Social Science Research Network Working Paper Series, 2007.
[44] J. MacQueen, in: Some methods for classification and analysis of multivariate observations, Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability, 1, University of California Press, 1967, pp. 281–297.

[45] S. Wasserman, K. Faust, Social Networks Analysis, Cambridge University Press, 1994.
[46] L. Kaufman, P. Rousseeuw, Finding groups in data: an introduction to cluster analysis, Wiley Series in Probability and Mathematical Statistics: Applied Probability and Statistics, Wiley, 1990.
[47] IDC Group Research Report, Technical Report, 2012.
[48] J. Bessen, M.J. Meurer, The Patent Litigation Explosion, Working Papers, Research on Innovation, 2005.

Hyoungshick Kim is a Post Doctoral fellow in the Department of Electrical and Computer Engineering at the University of British Columbia. He received a BS degree from the Department of Information Engineering at Sungkyunkwan University, a MS degree from the Department of Computer Science at KAIST and a Ph.D. degree from the Computer Laboratory at University of Cambridge in 1999, 2001 and 2012, respectively. He previously worked for Samsung Electronics as a senior engineer from May 2004 to September 2008. He also served as a member of DLNA and Coral standardization for DRM interoperability in home networks. His current research interest is focused on social computing and usable security.

JaeSeung Song is currently working as a senior standard researcher at NEC Europe Ltd. and a Ph.D. candidate at Imperial College London in the Department of Computing, United Kingdom. He holds BS and MS in Computer Science from Sogang University. He worked for LG Electronics as a senior research engineer from 2002 to 2008. He occupied leadership positions in 3GPP standard groups as rapporteur and contributor. His research areas include patent analysis, telecommunications, network management, intellectual property management and social networking.