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Characterizing Patent Assignees by Their Structural Positions Relative to a Field's Evolutionary Trajectory

Chung-Huei Kuan[a,c], Jia-Tian Lin[b], Dar-Zen Chen[b,c,*]

[a] Graduate Institute of Patent, National Taiwan University of Science and Technology, No. 43 Sec. 4 Keelung Rd., Taipei, Taiwan (R.O.C.)
[b] Department of Mechanical Engineering, National Taiwan University, No. 1, Sec. 4, Roosevelt Rd., Taipei, Taiwan (R.O.C)
[c] Center for Research in Econometric Theory and Applications, National Taiwan University, No. 1, Sec. 4, Roosevelt Rd., Taipei, Taiwan (R.O.C)

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ABSTRACT

This study characterizes and classifies the assignees of a technology field's patents through quantitatively determining their structural positions against a trajectory epitomizing the field's knowledge evolution. By considering that these patents' citation network embodies a knowledge structure for the technology field, and assuming that a series of *mainstream* (MS) patents constitute the evolutionary trajectory, each non-MS patent is identified to be at one of the following positions: *forward and backward reachable* (FBR), *backward reachable only* (BRO), *forward reachable only* (FRO), and *unreachable* (UR), based on their reachability with the MS patents. The assignees are then associated with five positioning attributes, which are the shares of their patents at respective positions. With precise definitions using these quantitative attributes, assignees of the technology field are classified into exactly one of the distinctly positioned categories, namely *trendsetters*, *contributors*, *absorbers*, *bystanders*, and *reinforcers*, or one of the multiply positioned categories of mixed characteristics. These categories can be geometrically interpreted and the assignees' positions can be visualized in a three-dimensional *positioning space*. This study then uses U.S. biochip patents and evolutionary trajectory derived by main path analysis (MPA) to observe how the proposed method work.

1. Introduction

Positioning generally means determining an entity's location in a physical system or a conceptual context, or relative to the other entities of the system or context. There are a vast amount of studies regarding various types of positioning, such as brand positioning (cf. Iyer, Davari, Zolfagharian, & Paswan, 2019), product positioning (cf. Chen & Ni, 2020), price positioning (cf. Xie & Kwok, 2017), even political positioning (cf. Griva & Chryssochoou, 2015), to mention just a few.

Such a positioning activity can offer a number of benefits. In addition to examining a specific entity's strategy or performance based on its position, similarly positioned entities may be clustered and assessed together, and distinctly positioned entity groups may be compared and contrasted with each other, all in a more efficient manner.

The present study emerges from the idea that whether a kind of positioning within a technology field can be quantitatively achieved, so that a large number of entities can be investigated and evaluated efficiently.

Patent citation (Hall, Jaffe, & Trajtenberg, 2005) is perhaps the most widely applied mechanism in studying development of a technology field. Patent citations are commonly considered as a route of knowledge diffusion from the cited to the citing patents, and a patent citation network, therefore, may be deemed to embody a knowledge structure of the technology field.

* Corresponding author.
E-mail addresses: maxkuan@mail.ntust.edu.tw (C.-H. Kuan), q02546013@ntu.edu.tw (J.-T. Lin), dzchen@ntu.edu.tw (D.-Z. Chen).

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Related prior works generally aggregate the patents of a patent citation network into entities at a higher level of granularity, so that the patent citation network is turned into a citation network of (1) the patents' assignees (i.e., the individuals or organizations whom the patent rights are assigned to); (2) the nationalities or residential countries of the patents' assignees or inventors; (3) the countries where the patent applications are filed; or (4) the patents' associated industry segments or technology fields. By aggregating patents into one of these types of entities and converting patent citations into entity citations, these prior works investigate key entities or closely collaborating entities, or explore the structures/patterns/characteristics of the knowledge transfer/flow/spillover/convergence between these entities.

These approaches are repeatedly applied in observing knowledge diffusion within various technology fields such as nanotechnology (Zheng, Zhao, Zhang, Chen, & Huang, 2014), LED (Chen, Huang, Hsieh, & Lin, 2011), organic photovoltaic cells (Choe, Lee, Seo, & Kim, 2013), RFID (Hung & Wang, 2010), printed electronics (Kim, Cho, & Kim, 2014), genetically modified crops (Ji, Barnett, & Chu, 2019), or among various geographical areas such as those within Taiwan (Cho & Shih, 2011), Asia (Tseng, 2009), or the world (Ribeiro, Kruss, Britto, Bernardes, & e Albuquerque, 2014; Ye, Zhang, Liu, & Su, 2015; Chen & Guan, 2016).

Following the same vein, the present study is aimed to qualitatively position the patent assignees of a technology field within the field's patent citation network or its knowledge structure.

2. Literature review

Regarding patent assignees' structural positions within a technology field, three main approaches may be identified from the literature. The first approach heavily relies on some network measures reflecting the structural features of the patents or entities, such as the various types of centralities. This type of approach may be broken down into two sub-types. The first identifies the higher-valued patents and then considers the assignees of these patents as "key players." Some exemplary works for this sub-type include Benson, Triulzi, and Magee (2018) where representative sets of 3D-printing patents are determined and their assignees are treated as top assignees, and Feng and Magee (2020), which located electrical vehicle related patents having higher knowledge persistence and considered their assignees as key assignees for the field.

The second sub-type of this approach directly works on the network of assignees derived from the patent citation network. Tsay and Liu (2020) derived assignee cooperation network of AI patents and identified the core assignees using degree and closeness centralities. Rongying, Xinlai, and Danyang (2020), using the assignee citation network, considered the assignees having higher numbers of assignees (called technology diffusion breadth) as having more important, fundamental, and influential technology. Within the framework of the above approach, Wang, Qiao, Wang, and Wan (2019) is a bit different. They first converted a patent citation network into a citation network of the patents' IPC codes. They then classified assignees into four types: providers, mediators, consumers, and negative mediators, based on the citation behaviors between their patents' IPC codes. For example, a mediator is one whose IPC codes having stronger diffusion and integration behaviors, and is considered to be actively disseminating and absorbing technological knowledge to and from other assignees.

The second approach positions assignees in a densely/strongly concentrated core or a loosely/weakly connected periphery following the core/periphery model (Borgatti & Everett, 2000). Bekkers and Martinelli (2012) looked into the network of assignees of 3G telecommunications patents and suggested that the assignees belonging to a dense and cohesive core are the key players with significant knowledge positions. Epicoco (2013) observed both assignees and their countries from clusters of strongly connected patents of semiconductor miniaturization technology, where these clusters are considered to have reflected major topics of the technology. Nordensvard, Zhou, and Zhang (2018) used wind turbine patents, separated assignees and their countries into those located in the core, periphery, and semi-periphery, and compared the knowledge flows between these three sectors. Chen and Guan (2016) is a bit different. Instead of aggregating patents into patent assignees, they separated patent inventors' residential countries into core and peripheral groups, and indicated that most of the knowledge flow happens between core countries whereas the flow between peripheral countries is both sporadic and weak.

The third approach first identifies an evolutionary trajectory of the field from the patent citation network, and positions the assignees relative to this evolutionary trajectory. Bekkers and Martinelli (2012) claimed that knowledge positioning in this way is better than positioning through the core/periphery structure, where their trajectory was derived using main path analysis (MPA) (Hummon & Doreian,1989). Epicoco (2013) used Critical Path Method (CPM), also a type of MPA, to derive a trajectory for the semiconductor miniaturization technology, and considered the trajectory as the technology's "backbone." Kim, Lee, and Kwak (2017) employed MPA to obtain a trajectory for machine-to-machine IoT patents and assumed that "there is a high degree of technology cumulativeness" along the trajectory.

Epicoco (2013) treated the patents along the derived trajectory as core patents, and reported that the organizations filing for these patents are indeed prestigious. Kim, Lee, and Kwak (2017) also observed the patents and their assignees located on the trajectory and their interaction with those clustered around the trajectory. For both prior works, patents along the trajectory and the assignees responsible for these patents are verified to have a more significant status using other bibliometric measures or industry observations.

In addressing knowledge positions of firms, Bekkers and Martinelli (2012) also thought that investigating firms that own the patents along the trajectory may provide insight to their unique knowledge positions. However, instead of just singling out those along the trajectory, they categorized assignees' patents into those "on trajectory," "contributing to trajectory," and "non-contributing" ones. The contributing-to-trajectory patents are those directly or indirectly cited by the on-the-trajectory patents. Bekkers and Martinelli (2012) then summed the shares of the first two types of patents as the assignees' knowledge position scores. They then reported that this new indicator reflects the historical and technical phenomenon of the field.

Due to the popularity of MPA in deriving trajectories in the above prior works, a brief review to MPA is outlined below. MPA is a network analytic method mainly for discovering one or more trajectories of a technological or research field manifested by its citation network. The basic assumptions of MPA are that a citation denotes the passage of knowledge from the cited to the citing documents, and that a citation's arc traversed more frequently between various pairs of document nodes is considered more critical in knowledge diffusion. MPA then identifies one or more series of end-to-end connected arcs in the citation network, called *main paths* (MPs). These MPs are deemed to reflect the evolution of the knowledge structure embodied in the citation network.

MPA has gained a growing popularity among researchers of diversified disciplines, probably due to that the popular network analysis software Pajek (Batagelj & Mrvar, 1998; De Nooy, Mrvar, & Batagelj, 2018) has MPA functions built-in. A quick query using Google Scholar with keywords "main path analysis" returns more than 400 publications since 2019. MPA is applied to a broad range of studies involving papers, patents, or both. The following is a very short list, where MPA was employed to detect research trend and technological development (cf. Fu et al., 2019; Park & Magee, 2017), to review a field's literature (cf. Barbieri, Ghisetti, Gilli, Marin, & Nicolli, 2016; Yan, Tseng, & Lu, 2018), and to identify research fronts and technological opportunities (cf. Kim & Shin, 2018; Liu, Lu, & Lu, 2016).

An additional caveat is that there are actually two types of patent citations: those identified by the examiners of patent offices (i.e., *examiner citations*) and those submitted by the inventors or applicants to the patent offices (i.e., *applicant citations*), and that there is a lack consensus concerning which type of citations is more reliable in reflecting the knowledge flow or influence of the cited to the citing. On one hand, Hegde and Sampat (2009) found that examiner citations are better value indicators as they are more strongly related to patent renewal probability than the applicant citations are. Cotropia, Lemley, and Sampat (2013) indicated that patent examiners rely almost exclusively on prior art they find themselves, instead of applicant citations, in rejecting patent applications or in limiting patent scopes. In other words, examiner citations are more related to patents' novelty and non-obviousness. On the other hand, Alcacer and Gittelman (2006) warned that examiner citations may add measurement error and using pooled citations may suffer bias. Criscuolo and Verspagen (2008) suggested that inventor citations, rather than the total set of citations, should be taken as indicators of knowledge flow. Park, Jeong, and Yoon (2017) argued that the quality of patents cited by applicants was higher than that of the patents cited by examiners.

Therefore, due to the lack of consensus, a patent citation network may be constructed using only examiner or application citations, or using both types of citations. For the latter, the examiner and application citations may be treated equally, or they may be given different weights based on some similarity measures between the cited and the citing (Kuan, Chiu, Liu, Huang, & Chen, 2018). Furthermore, patent citations involve an additional particularity where each utility patent application may result in two citable documents: a published patent application (PPA) before the application is granted and the patent after the application is granted (Kuan, Chen, & Huang, 2020). Then, the patent citation network may be built considering citations to the patents only, or together with citations to the PPAs as well. It should be noted that different evolution trajectories or MPs may be derived, depending on how the patent citation network is constructed.

The present study also intends to quantitatively position patent assignees of a technology field by identifying their patents' structural positions relative to one or more knowledge evolutionary trajectories of the field.

This study, however, differs from the prior works in following respects. Firstly, the present study believes that an assignee's position within the related knowledge structure involves not one but multiple characteristics, and these characteristics should be evaluated altogether. Therefore, instead of considering only those owing or contributing to the patents on the trajectories, the present study associates each assignee with five *positioning attributes*, reflecting five different positioning characteristics relative to the patents along the trajectories.

By integrally considering these positioning characteristics, the present study categorizes assignees into various *distinctly positioned* and *multiply positioned* types. For assignees of the former, they reveal a specific positioning characteristic whereas, for those of the latter, they manifest mixed positioning characteristics, relative to the field's trajectories. As a further differentiation from the prior work, these assignee positions are associated with a degree of absoluteness or relativity. Assignees of the same position then may be distinguished as absolutely or relatively positioned ones. As such, the present study offers finer and more comprehensive analyses than those of the prior works.

Additionally, the present study only requires that there are a number of patents, hereafter *mainstream* (MS) patents, epitomizing the knowledge evolution, regardless of how they are derived. In this way, this study is not tightly integrated with one specific method, such as MPA, for discovering the knowledge evolution of a technology field, as MPA alone may not be adequate in some circumstances. For example, when a technology field involves disruptive or breakthrough technology, an additional method other than MPA may be applied so as not to miss patents of these emerging technologies.

3. Methodology

3.1. Positioning attributes

For patents of a technology field or, correspondingly, their nodes in the citation network, the present study considers that each of them must be at one of five possible positions. First of all, as described above, the present study assumes that there are a number of MS patents reflecting the field's knowledge evolution. These patents are then said to be at MS positions. Fig. 1 is a portion of a real citation network constructed from patents of a technology field, and the MS patents are those denoted as black nodes (i.e., nodes 5, 7, 10, 18, 22, 23, 28, 31).

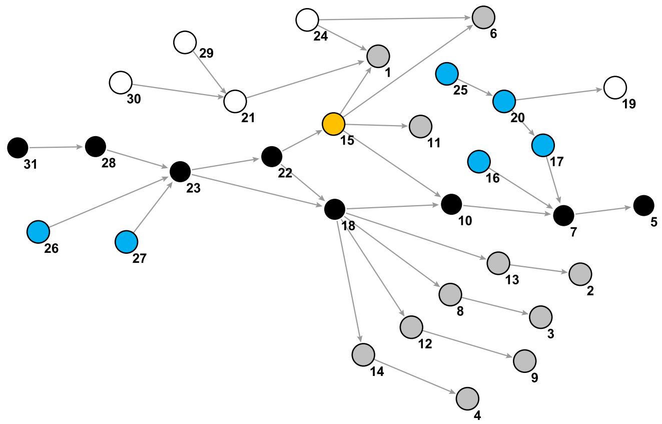

Fig. 1. A portion of a real patent citation network (black node: MS patent; white node: UR patent; grey node: FRO patent; blue node: BRO patent; orange node: FBR patent).

Once these MS patents are determined, each non-MS patent of the technology field can be positioned relative to these MS patents, based on its node's *reachability* with those of the MS patents. A patent citation network is normally acyclic and loop-less, and there must be either no path or at least a path of finite length between every pair of nodes of the network. Reachability between a pair of nodes *i* and *j*, then, can be defined as the following Eq. (1).

$$Reachable(i, j) = \begin{cases} 1, \text{ a path starting from } i \text{ ending at } j \text{ exists,} \\ 0, \text{ otherwise.} \end{cases} \tag{1}$$

An *unreachable* (UR) patent is one whose node cannot reach the nodes of the MS patents and vice versa. That is, an UR patent's node *i* satisfies the following Eq. (2).

$$\sum\nolimits_{\forall j \in MS} ((Reachable(i, j) + Reachable(j, i)) = 0. \tag{2}$$

From the knowledge diffusion's point of view, no knowledge originated from an UR patent would influence any MS patent and, likewise, no knowledge from the MS patents would influence the UR patent. In Fig. 1, UR patents are denoted as white nodes (i.e., nodes 19, 21, 24, 29, 30). Please note that patents are unreachable only relative to those MS patents. They should not be considered as insignificant ones as some may actually be mediators that bring knowledge from other disciplines to the field; they may even become differently positioned subsequently. This is also one of the reasons that the present study includes UR patents, instead of excluding them as in prior studies, in assignee positioning. In addition, the inclusion of UR patents also provides the degree of absoluteness or relativity of an assignee's position.

A *forward reachable only* (FRO) patent is one whose node cannot reach those of the MS patents but may be reached by at least a node of the MS patents. That is, a FRO patent's node *i* satisfies the following Eq. (3).

$$\sum\nolimits_{\forall j \in MS} Reachable(i, j) = 0, \ \sum\nolimits_{\forall j \in MS} Reachable(j, i) > 0. \tag{3}$$

The FRO patents, denoted as grey nodes in Fig. 1 such as nodes 1~4 and 11~14, can trace their knowledge provenance backward through the MS patents, and they are considered to be influenced by the knowledge of MS patents. The knowledge of a FRO patent, however, have no influence on the MS patents.

Backward reachable only (BRO) patents, denoted as blue nodes such as nodes 16~17 and 25~27, are those whose nodes may reach at least one node of the MS patents but not the other way around, contrary to the FRO patents. In other words, the knowledge of BRO patents influences at least one of the MS patents and, therefore, the evolution of the technology field. BRO patents, however, are not influenced by the knowledge of any MS patent. A BRO patent's node *i* satisfies the following Eq. (4).

$$\sum\nolimits_{\forall j \in MS} Reachable(i, j) > 0, \ \sum\nolimits_{\forall j \in MS} Reachable(j, i) = 0. \tag{4}$$

A patent whose node is both backward reachable from and forward reachable to at least one node of the MS patents, such as the orange node 15, is referred to as a *forward and backward reachable* (FBR) patent, and may be considered to have drawn knowledge from at least an earlier MS patent and then fed knowledge back to at least a later one. A FBR patent's node *i* satisfies the following condition (5).

$$\sum\nolimits_{\forall j,\, k \in MS} ((Reachable(j, i) \times Reachable(i, k)) > 0. \tag{5}$$

Compared to Bekkers and Martinelli (2012), their "contributing to trajectory" patents include the present study's BRO and FBR patents, and their "non-contributing" patents are the present study's FRO and UR patents combined together. The present study, therefore, claims earlier to have offered finer and more comprehensive details than the prior works did.

Some may question the necessity of FBR as it may be incorporated into the backward and forward reachable positions and attributes. The present study, however, believes FBR is unique in that a FBR patent has a double character and plays a feedback role

Table 1
Positioning attributes for a distinctly positioned assignee *i*.

	MS_i	FBR_i	BRO_i	FRO_i	UR_i
Trendsetter	> 0	< 1	< 1	< 1	< 1
Reinforcer	0	> 0	0	0	< 1
Contributor	0	0	> 0	0	< 1
Absorber	0	0	0	> 0	< 1
Bystander	0	0	0	0	1

in the field's evolution. Having such a position and attribute may lend analysts additional insight. For example, as the field evolves, an assignee's originally FRO-positioned patents may later become FBR-positioned ones. Then, an assignee's varying FRO and FBR attribute as time progresses may shed light on the assignee's shifting role from beneficiary to benefactor.

Each assignee *i*, after the positions of all its patents are identified, can be characterized by five *positioning attributes* (MS_i, FBR_i, BRO_i, FRO_i, UR_i), which are respectively the shares of its patents at the MS, FBR, BRO, FRO, and UR positions, where $0 \leq MS_i, FBR_i, BRO_i, FRO_i, UR_i \leq 1$ and $MS_i+FBR_i+BRO_i+FRO_i+UR_i = 1$. The assignee *i*'s each and every positioning characteristic relative to the MS patents is as such respectively captured by these attributes. In other words, an assignee's positioning attributes capture the multiple characteristics of its position within the knowledge structure embodied in the field's patent citation network.

Some words of caution are in order here. A technology field may involve, not one, but several evolution trajectories, perhaps some major and some minor ones. If the MS patents are from one, not all, of the trajectories, then, the patent positions and assignee attributes are actually measured relative to the MS patents of that particular trajectory.

3.2. Assignee classification

3.2.1. Distinctly positioned assignees

Once an assignee *i* has its positioning attributes (MS_i, FBR_i, BRO_i, FRO_i, UR_i) determined, it can be classified as one of a *distinctly positioned* assignee as defined in Table 1.

Trendsetters are assignees owning at least one MS patent, or having non-zero MS attribute. They are named as such because their one or more patents are actually part of the field's evolutionary trajectory, giving them a special status among all assignees. In real world, a trendsetter assignee is expected to be one that has provided important innovation or technology to the field, as suggested by Bekkers and Martinelli (2012), Epicoco (2013), and Kim, Lee, and Kwak (2017).

These trendsetting assignees can be ranked by the number of MS patents they own. Additionally, for assignees owing the same number of patents, they can be differentiated using their respective (1) $\mathrm{MS_i}$ values, (2) $MS_i+FBR_i+BRO_i$ values, referred to as *MS contribution values*, or (3) $MS_i+FBR_i+BRO_i+FRO_i$ values, referred to as *MS association values*, which respectively indicate an assignee's share of patents (1) being the MS patents, (2) not only being but also influencing the MS patents, and (3) not only being and influencing but also drawing influence from the MS patents. In short, these measures reveal the assignee's degrees of involvement with the MS patents.

Bystanders are those having only UR patents, or their UR attributes equal to one. That is, their patents are completely irrelevant to the MS patents from a knowledge diffusion perspective. An assignee's being a bystander does not imply that, in real life, it must have few patents or it is an insignificant player of the field. It is just that its patents do not seem to have knowledge exchange with the MS patents and the bystander assignee seems to be outside the field's development trend.

Prior studies often ignore bystander assignees altogether. There are assignees that do not qualify as bystanders but are very close, meaning the majority of their patents are UR-positioned. These quasi-bystanders do offer some hint regarding their positioning. Therefore, instead of ignoring them along with bystander assignees, the present study still classifies them according to their minor shares of non-UR patents.

Contributors are those having only BRO and UR patents and no MS, FBR, and FRO patent. They are so named because these BRO patents must lead ahead of and furnish knowledge to one or more MS patents. In real life, a contributor assignee is expected to be an earlier player of the field that have revealed noteworthy innovation or technology that "inspires" the MS patents, according to Bekkers and Martinelli (2012).

Contributor assignees may have varying degrees of contribution. The ones having only BRO patents and no UR patent (i.e., with attributes (MS=0, FBR=0, BRO=1, FRO=0, UR=0)) are hailed as *absolute* contributors, while the others have their contribution diluted by the UR patents down to the point where they are close to bystanders.

Following the same rationale, *absorbers* have only FRO and UR patents but no MS, FBR, and BRO patent. Their FRO patents must lag behind and draw knowledge from at least one of the MS patents; hence the name. There are also absolute absorbers having only FRO patents (i.e., with attributes (MS=0, FBR=0, BRO=0, FRO=1, UR=0)) and absorbers of low degrees of absorptance. An absorber is not necessarily an inferior assignee in real world and it may actually be a well-established player. Being an absorber may imply its research probably lags behind those of the trendsetter and contributors, or the technology is not one of its strengths. Bekkers and Martinelli (2012) ignore these absorbers but think they "plug the relevant knowledge" from the MS patents.

Reinforcers have only FBR and UR patents but no MS, BRO, and FRO patent. Their FBR patents not only draw knowledge from some earlier MS patents but also feedback knowledge to some later MS patents, as if they are reinforcing the field's evolution. Reinforcers

Table 2
Positioning attributes for a multiply positioned assignees *i*.

		MS_i	FBR_i	BRO_i	FRO_i	UR_i
Bi-positioned	Reinforcer/contributor	0	> 0	> 0	0	< 1
	Contributor/absorber	0	0	> 0	> 0	< 1
	Reinforcer/absorber	0	> 0	0	> 0	< 1
Tri-positioned	Reinforcer/contributor/ absorber	0	> 0	> 0	> 0	< 1

also may have varying degrees of reinforcement from absolute reinforcers to those quasi-bystanders. In real life, a reinforcer assignee is expected to be one entering the field not as early as the contributors but it is inspired and subsequently contributes to the field by some relevant innovation or technology.

3.2.2. *Multiply positioned assignees*

Unlike the distinctly positioned, an assignee *i* with positioning attributes (MS_i, FBR_i, BRO_i, FRO_i, UR_i) may not be classified as having a specific position, but it can be classified as one of a *bi-positioned* or *tri-positioned* assignee as defined in Table 2.

Bi-positioned assignees have patents located at two of the three FBR, BRO, and FRO positions and, therefore, there are three types of bi-positioned assignees: (1) those having mixed FBR and BRO patents, reflecting a mixed character of both contributor and reinforcer; (2) those having mixed BRO and FRO patents, reflecting a mixed character of both contributor and absorber; and (3) those having mixed FBR and FRO patents, reflecting a mixed character of both contributor and reinforcer. For one example, an assignee with positioning attributes (MS=0, FBR=0, BRO=0.50, FRO=0.50, UR=0) is a contributor and an absorber. An assignee with attributes (MS=0, FBR=0, BRO=0.03, FRO=0.77, UR=0.20) is another example of combined contributor and absorber. However, it can be seen that the former has equal contribution and absorptance, whereas the latter is oriented more towards and actually rather close to an absorber.

Tri-positioned assignees have all three types of patents in their portfolios and, therefore, a character combining contributor, absorber, and reinforcer. Assignees with attributes (MS=0, FBR=0.33, BRO=0.33, FRO=0.33, UR=0), and (MS=0, FBR=0.13, BRO=0.40, FRO=0.30, UR=0.17) are both tri-positioned ones. The latter, with a minor portion of FBR patents, inclines towards contributor and absorber.

It should be noted that the same type of bi-positioned or tri-positioned assignees may be further differentiated based on their degrees of involvement with the MS patents using the above-mentioned MS contribution values and MS association values.

It should also be pointed out that, while the trendsetter assignees are treated altogether as a special group as described above, they may alternatively be classified along with the other assignees by ignoring their MS attributes. In this way, there may be additional multiply positioned categories such that an assignee is bi-positioned as both a trendsetter and an absorber with attributes (MS=0.22, FBR=0, BRO=0, FRO=0.63, UR=0.15), or tri-positioned as trendsetter, reinforce, and absorber with attributed (MS=0.08, FBR=0.25, BRO=0, FRO=0.42, UR=0.25).

3.2.3. *Geometric Interpretation*

It is worth mentioning that, initially, considering the assignees as observations and their positioning attributes as observation variables, the present study tried principal component analysis (PCA), which is probably the oldest and best known multivariate analysis (Jolliffe, 2002), hoping that it would project the positioning attributes to a smaller number of uncorrelated variables for better assignee classification and visualization. The experiment, however, did not yield meaningful clusters of assignees that would lend themselves to intuitive explanation.

The method described above, in contrast, allows each assignee of a technology field to be classified into exactly one specific category. In addition, each non-trendsetter assignee can be represented and visualized as a point in a three-dimensional space, and assignees of various categories can be observed and interpreted geometrically.

In this *positioning space*, assignees' FBR, BRO, and FRO attributes are a corresponding point's coordinates against the space's three axes, as illustrated in Fig. 2. Then, the reinforcer, contributor, or absorber assignees are respectively denoted by points located along the FBR, BRO, or FRO axes, whereas bystander assignees, with zero FBR, BRO, and FRO attributes, are denoted by points all coinciding with the origin. A reinforcer, contributor, or absorber assignee's point would be located farther away from, or closer to the origin, if it inclines more towards an absolute one or a bystander.

As to the bi-positioned assignees, their respective points are located on the planes bounded by the FBR, BRO, or FRO axes. For example, assignees with attributes (MS=0, FBR=0, BRO=0.50, FRO=0.50, UR=0) and (MS=0, FBR=0, BRO=0.03, FRO=0.77, UR=0.20) are both combined contributors and absorbers, and they are both denoted by points on the BRO × FRO plane. The points are closer to the origin if their assignees' positions are more diluted by UR patents, and they are closer to one of the axes if the assignees are oriented more towards one of the characters.

Tri-positioned assignees' points are located within the space bordered by the axes and planes. Similarly, their distances to the origin and the FBR, BRO, and FRO axes signify the assignees' respective degrees of inclination towards the bystander, reinforcer, contributor, and absorber characters.

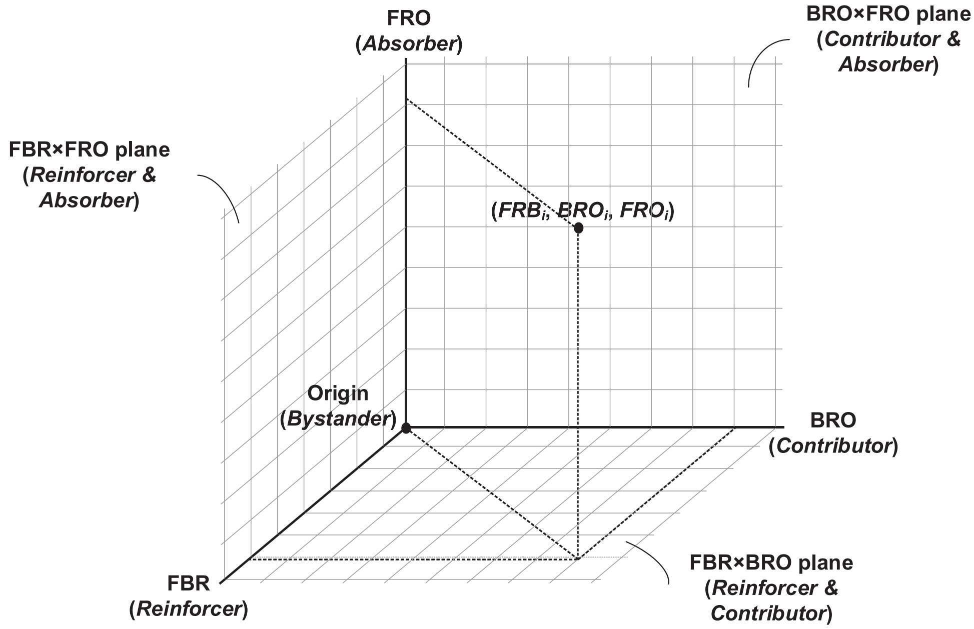

Fig. 2. The positioning space.

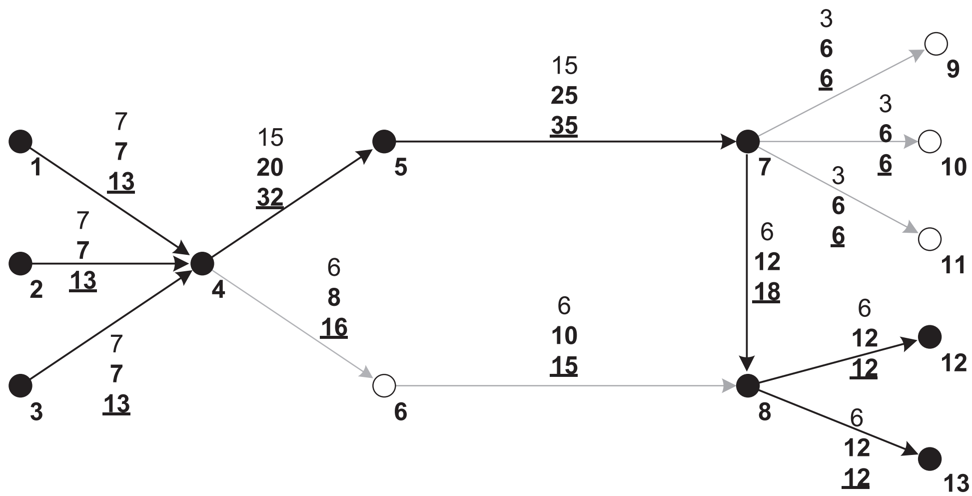

Fig. 3. A fictitious citation network with SPC, SPLC, and SPNP weights.

3.3. Main path analysis

In a subsequent empirical observation of the proposed knowledge positioning method, MPA is adopted to derive at least a trajectory from the patent citation network, and those chained along the trajectories are designated as the MS patents. The present study must emphasize again that it does not require that the MS patents to be determined by a specific method. MPA is chosen simply for its popularity.

MPA involves two major ingredients: weight assignment and path determination. After a directed and acyclic network is constructed from a set of papers or patents and their citations, each arc is assigned a weight based on its traversal count by various node pairs. Then, one or more chains of arcs are determined as the citation network's MPs based on their more significant arc weights.

To demonstrate MPA, Fig. 3 depicts a fictitious citation network whose arc weights assigned with algorithm *search path count* (SPC) (Batagelj, 2003), *search path link count* (SPLC), and *search path node pair* (SPNP) (both from Hummon and Doreian (1989)) are stacked besides them (the top, middle, and bottoms values are respectively the arc's SPC, SPLC, and SPNP weights). There are other weight assignment algorithms, such as Forward Citation Node Pair (FCNP) (Choi & Park, 2009), in addition to the three mentioned above. The three, however, are available from Pajek and, therefore, the most popular ones.

An arc's SPC weight is determined only by the numbers of *source* node (i.e., those having only outgoing arc(s)) and *sink* nodes (i.e., those having only incident arc(s)) reachable to and from the arc. Using the arcs 4→6 and 6→8 as an example, each of the three source nodes (1 to 3) will traverse the arcs two times to reach the sink nodes (12 and 13) and their arc weights are, therefore, both 6 (=3 × 2). On the other hand, SPLC considers all nodes that may reach the arc, not just the source nodes. Therefore, the arcs 4→6 and 6→8 have SPLC weights 8 and 10, as they respectively involve four (1~4) and five (1~4, 6) such *preceding* nodes to the same sink nodes (12 and 13). SPNP further considers all nodes that may be reached from the arc, in addition to the sink nodes. The arcs 4→6 and 6→8 then have SPNP weights 16 and 15, as they may respectively lead to four (6, 8, 12, 13) and three (8, 12, 13) such *succeeding* nodes from four (1~4) and five (1~4, 6) preceding nodes.

Path determination also involves different algorithms. *Global search* (Liu & Lu, 2012) selects one or more paths between source and sink nodes having the greatest accumulated weights. *Local search* starts from either source or sink nodes, and traces arcs with the greatest weights forward or backward iteratively (Hummon & Doreian, 1989). Both local and global searches have a variant call *key-route* (Liu & Lu, 2012) that first locates a number of highest weighted arcs (i.e., key-routes) and either traces both backward and forward iteratively as in local search (i.e., local key-route) or selects the paths from these arcs to the source and sink nodes of highest accumulated weights as in global search (i.e., global key-route).

The same MP of the network shown in Fig. 3 is derived using either global or local search algorithm, with or without involving key-route, and it includes the end-to-end connected dark arcs. There lacks a consensus regarding which path determination algorithm is better, and the present study chooses global search, for its taking the entire network into consideration, and without the key-route flavor, for simplicity's sake.

4. Data

The present study needs a real case to observe how the proposed method works. This empirical observation may reveal certain properties of the proposed method, for example, whether patents are comparably distributed among the five positions, whether there are more FRO patents than BRO patents, whether the assignees may be sufficiently distinguished, etc.

This empirical observation, however, is not intended as a proof or validation to the proposed method, which is rather difficult as there are no known structural positions for the assignees involved. However, for some assignees mentioned below, the present study does try to associate them with some publicly available industry information, suggesting that the assignee positions discovered by the present study do carry a whiff of truth about the assignees' industry performance.

The technology field chosen is biochip. A biochip is a set of diminished microarrays simultaneously performing hundreds of biochemical reactions in a few seconds for purposes from gene decoding to disease diagnosis. Biochip is selected as it satisfies the following criteria: (1) the technology has an appropriate length of history and a potential for future growth, so that an evolutionary trajectory can be derived and its analysis would of interest; and (2) there are an ample number of related patents, as well as citations among them, for appropriate analysis.

It is reported that the technology was developed since 1983 (Oyebola, Odueso, and Olugbemi, 2017), and considered to be one of the most promising technologies in the 21st century (Li, 2019), thereby satisfying our requirement (1).

The present study then chooses U.S. biochip utility patents for analysis. A technology field's U.S. patents are usually considered as an epitome to the field's overall progress, as U.S. is probably the most contested market for a technology and seeking U.S. patent protection is a common strategic move for competitiveness by worldwide developers. U.S. patents are also well known to have abundant citations due to that U.S. patent applicants are obligated to disclose all known prior arts, thereby fulfilling our requirement (2). Our dataset does not include published patent applications but only issued patents, as many U.S. patent applications are initially filed by employees and, when the applications are granted, the rights are then assigned to the employers[1]. Using issued patents, therefore, guarantees that their assignee information is readily available.

45,025 patents granted before 2019/3/31 are gathered from the official databases of United States Patent and Trademark Office (USPTO) using a few general keywords and high-level Cooperative Patent Classification (CPC) symbols[2]. Due to this loose search criterion adopted to guarantee a high recall rate, irrelevant patents are inevitably included. Among the 45,025 patents, there are 12,905 isolated ones, and the remaining 32,120 respectively form 1,071 connected components. The largest one has 29,134 interconnected patents, whereas the rest all consist of no more than 30 patents. The isolated patents and those in the small components are considered as noises and removed. The 29,134 patents in the largest component are reserved as our dataset and assignee disambiguation is carefully conducted[3]. It should be noted that, in other cases where the network consists of several components of comparable sizes, additional MPs can and should be discovered from components other than the one producing the single MP.

[1] U.S. published application data now include an Applicant field which may be used to identify the employers. But this field is available only to applications after 2013, according to our observation.

[2] The search criterion requires that a retrieved patent has (1) ("bio$" or "biologic$") in the Title or Claims, or (("bio$" or "biologic$") and ("chip$" or "array$")) in the Abstract or Specifications, and with G01N$, B01L$, C12Q$, Y10T$, B01J$ as one of its CPC symbols, were "$" is the wildcard character. USPTO routinely reclassify all patents using the latest version of CPC system once a month. The above search is applied to the patents' reclassified, or so-called "current CPC," symbols on 2019/3/31.

[3] The following steps are conducted in cleaning the assignee names: (1) converting all letters into upper-cased ones; (2) removing punctuation marks, extraneous blanks, and symbols such as "&@-:()" etc.; (3) removing suffixes commonly found in organization names, such as CORP, CO LTD, LLC, INC, GMBH, etc. in their full and abbreviated forms; (4) removing stopwords such as THE, FOR, AND, OF, A, IN, etc.; and (5) checking misspellings and inconsistent word orders.

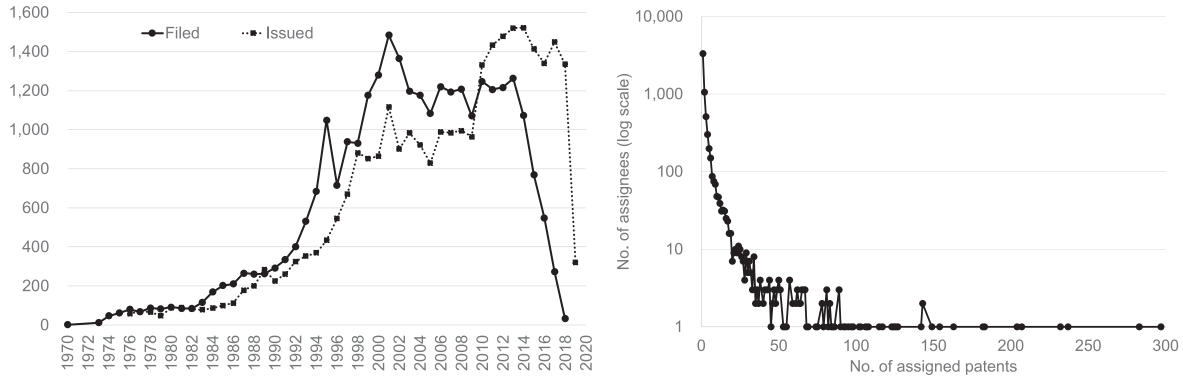

Fig. 4. Trends (left pane) and distribution of assignees (right pane) of the biochip patents.

Fig. 4 provides a summary to the 29,134 patents where the left pane shows trends according to their filing and issue dates, and the right pane presents the distribution of assignees according to their assigned patent counts[4]. The left pane reveals that there is a sharp growth in biochip patent applications starting from 1993 until 2001. The filing trend then slows down but there are still on average 1,200 annual filings until 2013. After that, filings drop significantly for the past few years. Even though the drop may be partially resulted from that applications in these years may still be pending, the slowdown of filings seems certain, considering that the drop starts as early as 2014. On average, there is a 3.42-year lag between these patents' filing and grant dates. Therefore, the issued-patent curve has not yet fully reflected the decreasing filings in the last few years. The sharp drop in the end is due to that the patents collected for the last year 2019 include only those granted before 2019/3/31.

The 29,134 patents involve 6,329 different assignees[5]. According to distribution shown in the right pane (with log-scaled vertical axis), there is a large number of assignees having only a few patents. Specifically, there are 3,332, or more than half, of the 6,329 assignees having only one patent. On the other hand, 346, or a mere 5%, of all assignees are assigned with fifteen or more patents, accounting for 15,107 or more than half of all patents. The Regents of the University of California has the greatest number of 544 patents and it is such an outlier that it is not included in the right pane of Fig. 4 so that the diagram is more readable.

A citation network is constructed using Pajek from the 29,134 patents and their citations. Due to the lack of consensus regarding the superiority of examiner or applicant citations described in the section Literature Review, both types of citations are included and treated equally. Also, as mentioned earlier, the dataset includes issued patents only and no published patent applications (PPAs) to guarantee the availability and accuracy of assignee information. The patent citation network is constructed excluding the citations to the PPAs.

Then, a MP illustrated in Fig. 5 is derived using MPA, and those chained along the MP are designated as the MS patents. It should be emphasized again that the present study does not require that the MS patents to be determined by a specific method. MPA is chosen here simply for its popularity, not because it is considered as the only or best method.

Among the weight assignment algorithms, SPNP is selected by the present study as it is more comprehensive in modeling knowledge diffusion (Kuan, 2020). The present study has tried global standard, global key-route (with 1 key route), local forward, local backward, and local key-route (with 1 key route) search algorithms. They produce very close MPs, except the one from the local backward search. The global standard and global key-route both obtain the same 22-node MP. The local forward and local key-route also derive 22-node MPs but differ from the global one respectively at 1 and 3 nodes. The local backward produces a 21-node MP whose 10 nodes are identical to those along the second half of the global MP. The present study chooses the global MP shown in Fig. 5 as it seems to be the largest common denominator by various algorithms[6]. Therefore, there are total 22 MS patents along the MP, whose filing dates, issued dates, and full assignee names are listed in the Appendix.

After the MS patents of Fig. 5 are identified, the position of every non-MS patent in the patent citation network is determined based on its reachability relative to the MS patents using the R package iGraph (Csardi & Nepusz, 2006) as follows. If a patent is only reachable to or from any MS patent, the patent is a BRO or FRO patent; if a patent is both reachable to and from any MS patent, it is a FBR patent; and, if a patent is not reachable neither to nor from all MS patents, it is an UR patent. Then, after the positions of all

[4] For simplicity's sake, full counting is used so that, for a patent co-assigned to two or more assignees, each assignee's patent count is added by one.

[5] Among the 29,134 patents, there are 1,511 patents whose gathered bibliometric data do not include assignee information. As to the 27,623 patents that do have assignees information, they involve 6,329 different assignees. 366 of the 27,623 patents are assigned to more than one assignee.

[6] The present study has also tried using SPC and SPLC weights. With the global standard and global key-route, the same MP as shown in Fig. 5 is obtained. The local forward and local backward, under SPC and SPLC weights, all add 15 nodes fanning out from the end, and 1 to 3 different nodes to the main trunk, of the MP of Fig. 5. The local backward has 12 and 11 identical nodes, respectively with SPC and SPLC weights, to those along the second half of the global MP of Fig. 5.

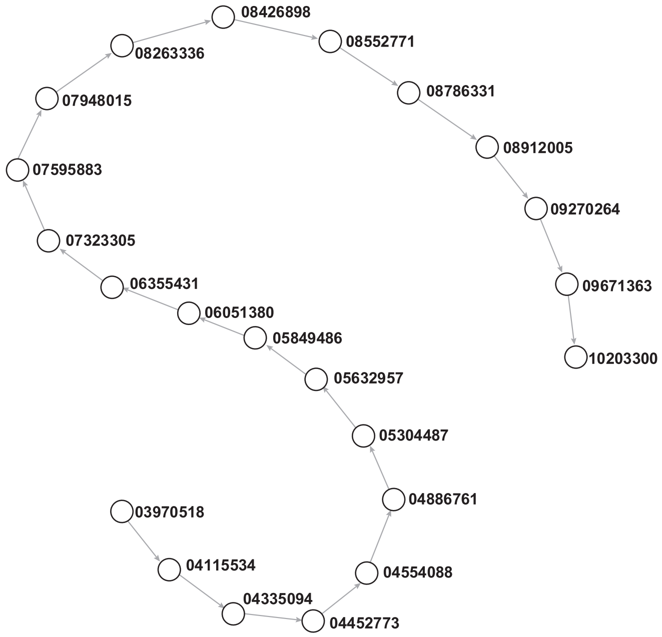

Fig. 5. Main path of the biochip patents.

Table 3
Biochip patents at various positions.

Total	MS	FBR	BRO	FRO	UR
29,134 100%	22 0.076%	639 2.19%	1,721 5.91%	11,814 40.55%	14,938 51.27%

Table 4
Distribution of distinctly positioned assignees.

Total	Trendsetter	Reinforcer	Contributor	Absorber	Bystander
5,974 (94.39%)	11 (0.17%)	40 (0.63%)	399 (6.30%)	2,367 (37.40%)	3,157 (49.88%)

patents are determined, their assignees' positioning attributes can be easily calculated. The respective numbers of patents at various positions are summarized in Table 3.

As shown in Table 3, the patents are not evenly distributed among these positions. The significant simplification achieved by MPA leads to mere 22 MS patents out of a total of 29,134 patents, about 0.076% reduction. From this small set of MS patents, there would be few FBR patents as well, as each FBR patent needs to involve two MS patents. Table 3 also suggests that a patent is more possible to be drawing knowledge from its field's MS patents (i.e., FRO-positioned) than to influence them (i.e., BRO-positioned). The dominant share of UR patents is also due to the significant reduction by the MPA. The present study speculates that this 51% of patents may involve some secondary evolutional trajectories parallel to the MP discovered. Despite that the MP may not be all encompassing, the present study, however, decides to stick to these 22 patents. The large number of UR patents also suggests that they should not be overlooked entirely.

5. Analysis

5.1. Distinctly positioned assignees

After obtaining all assignees' positioning attributes, the present study then identifies 5,974 distinctly positioned assignees, as shown in Table 4.

Distinctly positioned assignees constitute a high share, about 94% of all assignees, as there are a great number of assignees, 3,332 to be exact, owning a single patent and they are naturally distinctly positioned. Together with the large number of UR patents and few FBR patents, as indicated in Table III, there are as many as 3,157 bystanders and as few as 40 reinforcers. Similarly, due to this case has much more FRO patents than BRO patents, there are more absorbers than contributors.

Table 5
List of trendsetter assignees.

Assignee	MS Patents	All Patents	MS	FBR	BRO	FRO	UR	MCV	MAV
Life Technologies, Inc.	9	283	0.03	0.18	0.02	0.58	0.19	0.23	0.81
Nanogen, Inc.	3	86	0.03	0.38	0.10	0.44	0.03	0.52	0.97
454 Life Sciences Corporation	1	12	0.08	0.25	0.00	0.58	0.08	0.33	0.92
Advanced Magnetics Inc.	1	10	0.10	0.50	0.00	0.40	0.00	0.60	1.00
The Board of Trustees of Leland Stanford Junior University	1	154	0.01	0.04	0.04	0.49	0.43	0.08	0.57
Canadian Patents and Development Limited	1	1	1.00	0.00	0.00	0.00	0.00	1.00	1.00
General Electric Company	1	127	0.01	0.00	0.13	0.52	0.35	0.13	0.65
Illumina, Inc.	1	143	0.01	0.09	0.01	0.89	0.01	0.10	0.99
Minnesota Mining and Manufacturing Company	1	61	0.02	0.00	0.23	0.00	0.75	0.25	0.25
Trustees of the University of Pennsylvania	1	65	0.02	0.12	0.03	0.34	0.49	0.17	0.51
Yellowstone Diagnostics Corporation	1	2	0.50	0.00	0.50	0.00	0.00	1.00	1.00

Table 6
Distribution of multiply positioned assignees.

Total	Reinforcer/ Contributor	Contributor/ Absorber	Reinforcer/ Absorber	Reinforcer/ Contributor/ Absorber
355 (5.61%)	20 (0.32%)	165 (2.61%)	86 (1.36%)	84 (1.33%)

The 22 MS patents are assigned to 11 trendsetter assignees[7] whose respective positioning attributes, MS contribution values (MCVs), and MS association values (MAVs) are listed in Table 5 in decreasing order of the numbers of MS patents they own.

These 11 trendsetter assignees would traditionally be considered as holding especially important status as their patents jointly fashion the field's evolution. Among them, Life Technologies is assigned with the greatest number of MS patents. The company was founded in late 2008 through a US$6.7 billion merger and later acquired by Thermo Fisher for US$ 13.6 billion in 2014[8]. Its acquisition by more established incumbent players and the large monetary transactions involved implies its advanced capability in the industry. Nanogen, having the second largest number of MS patents, was named in the early days of the field (Tadmor, 1997).

The MCVs and MAVs may provide additional insight, especially for those having the same number of MS patents. For example, other than Life Technologies and Nanogen, the other 9 trendsetter all having a single MS patent. Among them, three companies immediately stand out by their greater-than-0.9 MAV values, indicating that they are more tightly related to the field's evolution than the other single-MS-patent assignees[9]. 454 Life Sciences was awarded the Wall Street Journal's Gold Medal for Innovation in the Biotech-Medical category in 2005 and acquired by Roche in 2007 for US$ 154.9 million[10]. Illumina, a publicly traded California-based company, specializes in systems for analyzing genetic variation and biological function, and was named one of the 50 smartest companies by MIT Technology Review in 2014[11]. Advanced Magnetics, also a public-traded company based in Massachusetts, is now called AMAG Pharmaceuticals, Inc. The company is recently acquired by Covis Pharma Group for US$ 498 million.[12]

Compared to 454 Life Sciences and Illumina, Advanced Magnetics has a greater MCV value, which is even higher than those of Life Technologies and Nanogen. In addition, Advanced Magnetics also has the highest MAV value among these five companies. These suggest that this company, even though it does not hold the highest number of MS patents, can be considered to have a more concentrated trendsetting capacity than the others.

Reinforcer assignees of this case seem to own a limited number of patents. In this case, each of all 40 reinforcers has no more than five patents and no more than three FBR ones. Bio-Metric Systems, one of the reinforcers whose all three patents are FBR ones (i.e., it is an absolute reinforcer), is now called Surmodics, Inc., a publicly traded company in Minnesota and a leading provider of chemical components for in vitro diagnostic (IVD) immunoassay tests and microarrays[13].

Biocircuits Corporation and Molecular Tool Inc. are contributors having more than one patent (10 and 7 patents, respectively) and the highest BRO attributes (0.90 and 0.86, respectively). Biocircuits was a publicly traded startup specializing in IVDs and is now defunct. Molecular Tool were also noticed in the early days of the field (Tadmor, 1997).

5.2. Multiply positioned assignees

The remaining 355 assignees are all multi-positioned ones, and their distribution among various categories is shown in Table 6. Again, due to the small number of FBR patents, the bi-positioned and tri-positioned categories involving reinforcer character have fewer members.

[7] The patent 04335094 does not have assignee information in its bibliometric data.
[8] See https://en.wikipedia.org/wiki/Life_Technologies_(Thermo_Fisher_Scientific).
[9] Canadian Patents and Development Limited and Yellowstone Diagnostics Corporation are ignored here as they respectively have only one and two patents.
[10] See https://en.wikipedia.org/wiki/454_Life_Sciences.
[11] https://en.wikipedia.org/wiki/Illumina,_Inc.
[12] https://en.wikipedia.org/wiki/AMAG_Pharmaceuticals.
[13] https://www.surmodics.com.

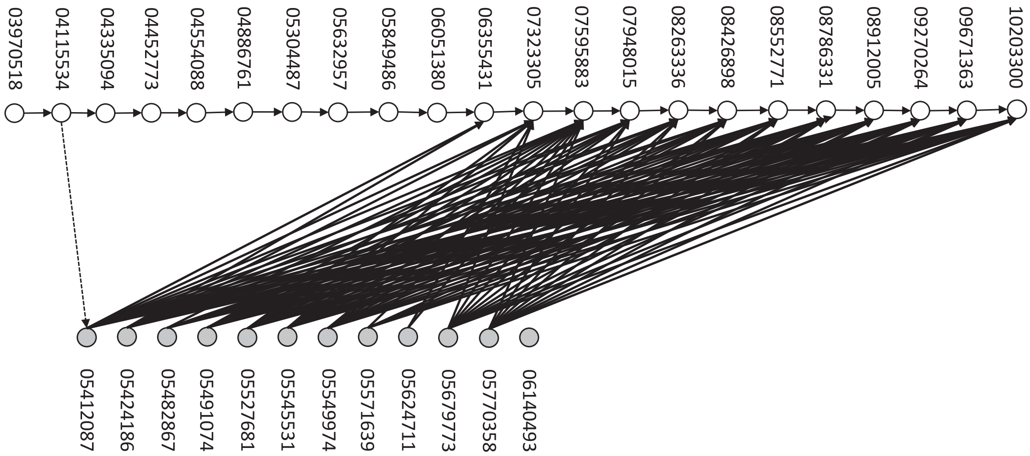

Fig. 6. The positions of Affymax Technologies' patents.

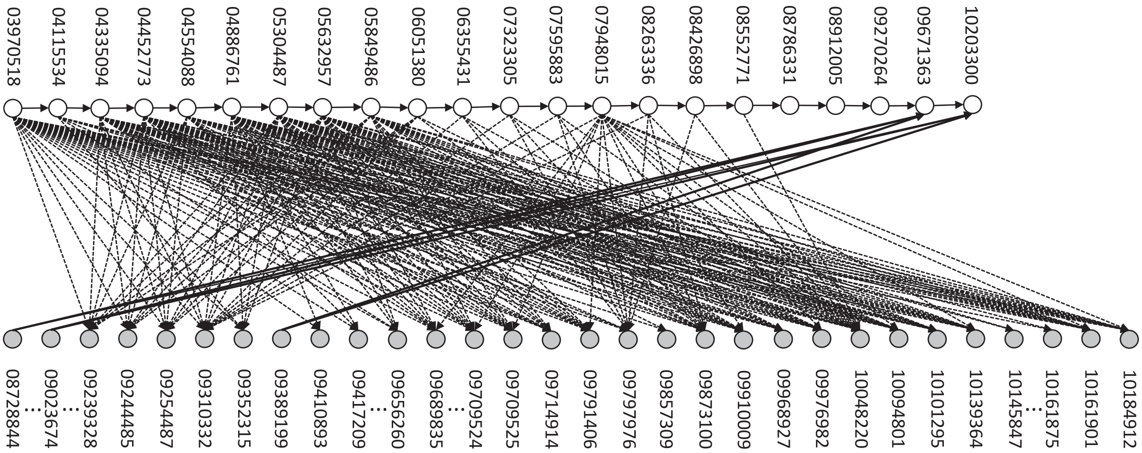

Fig. 7. The positions of Taiwan Semiconductor Manufacturing Company's patents.

An exemplary reinforcer/contributor, Affymax Technologies, is depicted in Fig. 6. This company, with 12 patents and attributes (MS=0, FBR=0.083, BRO=0.83, FRO=0, UR=0.083), is an early participant also mentioned in Tadmor (1997). In Fig. 6, the company's patents are denoted as grey nodes arranged along the lower part, the MS patents, as white nodes, are aligned in the upper part, and the thin arrows in between indicate reachability and direction. As illustrated, Affymax Technologies has almost all of its patents repeatedly influencing a later phase of the field's evolution, thereby strongly inclined towards a contributor. This public traded biopharmaceutical company did have a glory history, especially when it was acquired by British drug giant Glaxo for US$ 533 million as early as 1995[14].

An example of the contributor/absorber assignees is Taiwan Semiconductor Manufacturing Company (TSMC), having 36 patents with positioning attributes (MS=0, FBR=0, BRO=0.083, FRO=0.75, UR=0.17). The positions of its patents relative to the MS patents are depicted in Fig. 7. As illustrated, TSMC is indeed a combined contributor and absorber, and inclines towards an absorber. Such a position should be close to TSMC's industry perception. As the world's largest semiconductor foundry, TSMC does meagerly contribute to the development of biochip technology, but is more influenced by other dedicated biochip developers.

Hyseq Inc. is one of the 84 tri-positioned assignees with attributes (MS=0, FBR=0.10, BRO=0.80, FRO=0.10, UR=0) and strongly inclines toward a contributor. The company, specializing in DNA array technology, was merged into Nuvelo Inc., a biopharmaceutical company, who in turn was acquired by ARCA Biopharma, Inc.[15]

The positioning space provides not only visualization but also additional insight to the classifications of assignees. Using the BRO × FRO plane of the positioning space shown in Fig. 8 as an example, the assignees may be observed as follows. Firstly, the 2,367 absorbers are those denoted by the light blue points along the vertical FRO axis. To these assignees, they can be further differentiated based on how strongly they are positioned as absorbers reflected by the distances of their nodes from the origin. For assignees whose

[14] https://www.sfgate.com/business/article/British-Drug-Giant-Glaxo-to-Buy-Affymax-Palo-3047531.php.
[15] https://en.wikipedia.org/wiki/Nuvelo.

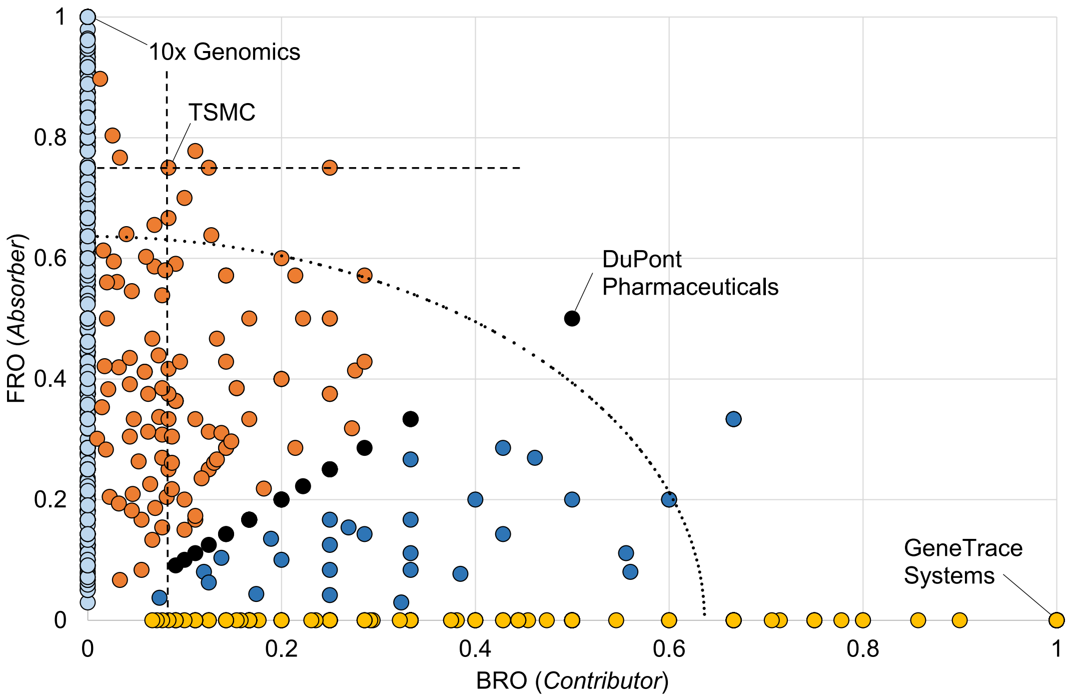

Fig. 8. Assignee distribution on the positioning space's BRO × FRO plane.

nodes are located farther away from the origin, their positions are less diluted by UR patents and a stronger absorber tendency is revealed. For example, 10x Genomics, a public traded company[16], is one of the absolute absorbers located farthest away from the origin. Similarly, the 399 contributors are represented by the yellow points along the horizontal BRO axis and those assignees whose nodes are more distant from the origin have stronger contributor positions. For example, GeneTrace Systems, an absolute contributor whose all four patents are BRO ones, was also noticed in the early days of the field (Tadmor, 1997).

Other than these distinctly positioned assignees, the points on the BRO × FRO plane denote the 165 bi-positioned contributor/absorber assignees with TSMC indicated. These assignees of dual positioning characteristics can be further classified into three groups. The 27 black points along the 45-degree line denote assignees with identical FRO and BRO attributes, thereby revealing equal inclination towards contributor and absorber. Again, their points' distances from the origin indicate the strength of their bilateral positions. For instance, DuPont Pharmaceuticals is an absolutely bi-positioned assignee. The company was acquired by Bristol-Myers Squibb Company for US$ 7.8 billion in 2001[17].

Then, the blue and orange points respectively above and below the diagonally aligned black points stand for two subsets of the bi-positioned assignees: a set of 107 assignees, as orange points, whose BRO attributes are less than their FRO attributes, and another set of 31 assignees, as blue points, whose BRO attributes are greater than their FRO attributes. For these assignees, their positions can be observed from two viewpoints. The assignees whose points are located closer to FRO or BRO axis are oriented more towards absorbers or contributors, respectively. Additionally, their points' distances from the origin also reveal the degree of dilution of their positions by UR patents. Again using TSMC of Fig. 7 as an example, its position is clearly manifested more as an absorber (i.e., its point is rather close to the FRO axis) and this position is mildly diluted by few UR patents (i.e., its point is closer to (0, 1) than to the origin).

There are also various other interesting observations with the positioning space shown in Fig. 8. For one observation, the assignees can be partitioned into subsets according to their points' distances relative to the origin by drawing concentric curves with the origin as the center. One exemplary dashed curve in Fig. 8 separates the points on the axes and in the plane into two sets of equal size. For those whose points are located inside the curve, their positions as contributor, absorber, or contributor/absorber are weakened by higher shares of UR patents and, therefore, not as evident as those whose points are outside the curve.

For another observation, an assignee can be selected as a reference and a crosshair is drawn with the reference assignee at the intersection. Then, the other assignees can be observed relative to the reference assignee. Again using TSMC as an example, assignees whose points are located within the four quadrants are those showing, relative to TSMC, stronger absorber-and-contributor positions (1st quadrant), stronger absorber but lesser contributor positions (2nd quadrant) (e.g., 10x Genomics), lesser absorber-and-contributor

[16] https://en.wikipedia.org/wiki/10x_Genomics.
[17] https://www.pharmaceuticalonline.com/doc/bristol-myers-squibb-acquires-dupont-pharmace-0001.

positions (3rd quadrant), and stronger contributor but lesser absorber positions (4th quadrant) (e.g., DuPont Pharmaceuticals and GeneTrace Systems).

In a practical context, a technology manager of an enterprise can determine his/her company's knowledge position within a technology field using the company's positioning attributes alone, or relative to other competitors as discussed above using the positioning space. The technology manager can also assess a large number of assignees altogether for decisions in licensing arrangement, collaboration, and merger. For instance, a candidate of a more contributor and reinforcer position is probably more desirable than one of a more bystander or absorber position. Similarly, a policy maker can also utilize the methodology provided by this study to evaluate how domestic enterprises and institutes perform in their specialized industries and allocate funding or resource to further strengthen those already in the contributor positions, or to subsidy those in the absorber position to catch up.

6. Conclusion and Discussion

In the present study, by considering that a technology field's patent citation network embodies a knowledge structure for the field, and that a series of patents epitomizing the evolution of the knowledge structure, each patent is identified to be at one of five possible positions relative the series of patents, namely *mainstream* (MS), *forward and backward reachable* (FBR), *backward reachable only* (BRO), *forward reachable only* (FRO), and *unreachable* (UR).

The patent assignees are then associated with five positioning attributes, which are the shares of their patents respectively at the five positions. Using these quantitative attributes, each assignee is classified into exactly one of the categories of distinct characteristics called *trendsetters*, *contributors*, *absorbers*, *bystanders*, and *reinforcers*, or one of those of mixed characteristics. These categories can be geometrically interpreted with a three-dimensional *positioning space* and the classified groups of assignees can be visualized in the space. The proposed method is then applied to U.S. biochip patents whose evolutionary trajectory is derived with main path analysis (MPA).

The greatest limitation of this method lies in its static nature, meaning that the patents of a technology field are gathered and analyzed at a single epoch of time. The field's patent citation network is actually an evolving structure as new patents and citations are continuously added to the network as time progresses. During this dynamic process, smaller and separate components in an early stage may be later connected into larger components. Not only an early evolution trajectory may be extended, but also an entirely different trajectory may emerge later. As the evolution trajectory varies through time, patents' positions relative to the trajectory may also vary, as well as the roles of the assignees. An early UR patent may become a MS patent later, and a later contributor assignee may be a bystander in the field's early stage. Therefore, the method can be enhanced by observing how the patent and assignee positions evolve along different development phases of the technology field. The assignees' changes of roles as they undergo these development phases would shed additional insight into these assignees' behavior or performance.

Some additional shortcomings of the proposed method are as follows. Firstly, there is an obvious difference between, for example, two BRO patents where one is backward reachable from few MS patents, whereas the other is backward reachable from more MS patents. In other words, the present study ignores the number of MS patents involved in identifying patent positions. Then, at the assignee level, the proposed method also fails to differentiate, for example, two contributor assignees where one contributes to only a handful of MS patents whereas the other contributes to most of them.

Another drawback is that, even for similarly positioned assignees involving comparable numbers of MS patents, the proposed method ignores where the reachable MS patents are located along the field's evolution. Taking Fig. 7 as an example, TSMC is influenced mostly by earlier MS patents, and it should be different from another assignee which is influenced mostly by later MS patents. Similarly, if it is TSMC's later patents that are influenced and TSMC again should be different from those whose early patents are influenced. In other words, the method fails to consider how early and later MS patents interact with early and later patents of an assignee.

Furthermore, the proposed method also ignores a patent's distance (e.g., number of "hops") to the MS patents. Therefore, it cannot tell whether some assignees are more closely influenced by or contributing to the MS patents than others. A final limitation of this study lies in how the patent citation network is constructed. In this study, the patent citation network includes only cited/citing patents of a technology field, and those cited and citing patents outside the field are omitted. This omission would inevitably affect at least some of the arc weights and, as such, the derived MPs. Using an extended network including those patents outside but reachable with those of the technology field for MPA could offer additional insight to the field.

This work is the authors' initial endeavor in characterizing patent assignees relative to a technology field's evolutionary trajectory. The above described shortcomings will be addressed in future projects on the foundation established by the present study. For example, one future project is, for a group of similarly positioned assignees classified by the proposed method, to incorporate the distance and time relationship between their patents and the MS patents into their positioning attributes so as to more accurately characterize these assignees.

CRediT authorship contribution statement

Chung-Huei Kuan: Conceived and designed the analysis, Collected the data, Contributed data or analysis tools, Performed the analysis, Wrote the paper. **Jia-Tian Lin:** Conceived and designed the analysis, Collected the data, Contributed data or analysis tools, Performed the analysis. **Dar-Zen Chen:** Conceived and designed the analysis, Contributed data or analysis tools, Wrote the paper.

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Appendix: List of 22 mainstream patents

Patent	Filing Date	Issued Date	Assignee Full Name
03970518	1975/7/1	1976/7/20	General Electric Company
04115534	1977/6/20	1978/9/19	Minnesota Mining and Manufacturing Company
04335094	1979/1/26	1982/6/15	Inventors: Mosbach; Klaus H. (this patent has no assignee information)
04452773	1982/4/5	1984/6/5	Canadian Patents and Development Limited
04554088	1983/5/12	1985/11/19	Advanced Magnetics Inc.
04886761	1987/3/26	1989/12/12	Yellowstone Diagnostics Corporation
05304487	1992/5/1	1994/4/19	Trustees of the University of Pennsylvania
05632957	1994/9/9	1997/5/27	Nanogen, Inc.
05849486	1995/9/27	1998/12/15	Nanogen, Inc.
06051380	1997/12/5	2000/4/18	Nanogen, Inc.
06355431	2000/3/3	2002/3/12	Illumina, Inc.
07323305	2004/9/22	2008/1/29	454 Life Sciences Corporation
07595883	2003/9/16	2009/9/29	The Board of Trustees of the Leland Stanford Junior University
07948015	2007/12/14	2011/5/24	Life Technologies Corporation
08263336	2011/5/31	2012/9/11	Life Technologies Corporation
08426898	2010/1/22	2013/4/23	Life Technologies Corporation
08552771	2013/4/22	2013/10/8	Life Technologies Corporation
08786331	2013/3/13	2014/7/22	Life Technologies Corporation
08912005	2014/7/17	2014/12/16	Life Technologies Corporation
09270264	2014/7/17	2016/2/23	Life Technologies Corporation
09671363	2015/11/12	2017/6/6	Life Technologies Corporation
10203300	2016/2/22	2019/2/12	Life Technologies Corporation

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