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Brownian agent-based technology forecasting☆

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ABSTRACT

Today's innovation process is best characterized by nonlinearity and interaction. Agent-based models build on these concepts, but have not been useful in practice because they are either too complex or too simple to make a good match with reality. As a remedy, we employ a Brownian agent model with intermediate complexity to produce value-added technology forecasting. As an illustration with Korea's software industry data, computer simulation is carried out. Attracted by higher technology value, agents concentrate on specific technology regions, and form co-existing major technology regions of high density. A rough comparison with actual software production data exhibits a fair reflection of reality, and supports the underlying idea that economic motivation of agents should be considered.

1. Introduction

Today's world economy depends on technology and its change to an extraordinary degree. In 2003, the Organization for Economic Cooperation and Development (OECD) expenditure on R&D (research and development) reached almost 680 billion dollars, and amounted to 2.2% of the total GDP over the OECD area [1]. With hard evidence on other indicators, it is widely accepted that technology should be a key factor contributing to economic growth in any economy. This is not a new phenomenon per se, but it has become more pervasive, mainly driven by substantial public and private returns. Previous studies have reported that the average return on R&D might fall between 25 and 35% in most firms, and beyond 70% on the public side [2]. Despite these impressive figures, new technology development is highly risky, and failure can lead to huge loss. Thus, to secure return, it is crucial to address what is likely to happen in the future with regard to technology development.

So far, a number of technology forecasting methods have been proposed, but they are forced to face a serious challenge in terms of accuracy. First and foremost, it should be noted that technology forecasting is premised on a certain orderliness of the innovation process [3]. From the outset, the innovation process models were basically singular in nature with linear assumptions. However, the evolution of these models points toward a complex network strongly oriented to interactions with nonlinear assumptions. Not surprisingly, previous forecasting methods such as trend extrapolation have become obsolete without a fair reflection of those innovation characteristics. Second, earlier methods give a single deterministic number as the forecast. By contrast, the high uncertainty associated with technology future makes it necessary to give a range of outcomes and the probability distribution over that range. Deterministic methods should be of limited use, while probabilistic forecasts would increase in share. Some people argue that judgmental or consensus method, e.g. Delphi, should be relatively free from the above-mentioned constraints, and a better method [4]. However, doubts on the accuracy of these methods have been cast unceasingly [5,6]. Considering this, there is a perception that an entirely new set of approaches to technology forecasting need to be invented [7].

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Although a wide variety of suggestions and issues have been presented, there has recently been an increasing interest in the application of agent-based models. Over the last decade, agent models, which had been developed in the artificial life community [8], have been an appropriate tool for describing social and economic interaction [9–11]. Interaction and linkages have been regarded as key ingredients of technology development but have not been described in a quantitative way. The very notion of agent models builds on interactions, and can give us a better chance of capturing many essential mechanisms. Another crucial feature, nonlinearity, is also reflected well. In agent models, it is assumed that history would be a poor guide for the future of nonlinear systems. Actually, the replication of past would be an impossibly stringent criterion for recent technology development. Being methods that will fit future data rather than past data, the agent model provides a good match with reality. Last but not least, the strength of this model is drawn from the flexibility to make a sensitivity test quite simple. Modifying the rules of agents to the extent possible, we can obtain the range and distribution of outcomes easily in line with the increasing demand for probabilistic forecast. Suffice it to say that the increasing complexity of recent technology development should call for more complex approaches such as agent models.

With due consideration to these advantages, the current paper aims at adapting an agent model of interactive structure formation to the problem of technology development, and further forecasting. However, this study draws on the design of agents to determine whether the agent model can describe the complex phenomena or not. The earlier complex agent concept was more typical of human thought and behavior. This agent can perform complex actions such as learning and building its own strategy with multiple attributes [12]. Pushing a bit further, the complex agent model in the neoclassical economic theory assumes that decisions of agents are made using complete a priori information. That is, an agent has complete knowledge of all possible actions and outcomes by itself and all others [13]. The conceptual design of complex agents is ideal but impractical. Given the freedom to define rules and interactions of agents infinitely, the possible number of combinations will soar to an eye-popping level. With ten agents and six rules, the number of possible states amounts to one million. The alternative is the minimalistic agent, which simply reacts to signals from the environment without referring to internal attributes. Unfortunately, the practical application of such an agent is also very limited due to oversimplification.

Avoiding both extremes, we employ an active Brownian agent approach (Fig. 1). Brownian agents are minimalistic in the sense that they act on the simplest set of rules without deliberative actions [11]. Through specific action and interaction, Brownian agents generate a self-consistent field which in turn influences their further behavior. That is, they do not respond passively to external forces but are actively involved in a nonlinear feedback process. It also implied implicitly that the focus should be more on interaction than autonomous action. The circular causation between agents and fields lead to the interactive structure formation and observed complex phenomena on the macroscopic level. It is very attractive that we can achieve a deeper understanding of complex phenomena based on a kind of reductionist approach regarding agents and their interactions. In the case of technology development, active Brownian agents have core advantages such as interaction and nonlinearity.

When applied to technology development, active Brownian agents are defined to be current and potential technology developers with two internal states. Agents who are willing to develop a specific technology generate the technology value field while tied to a specific technology. On the other hand, agents who are not willing to develop a technology can pursue other technology development opportunities with higher value in the vicinity under information constraints. Furthermore, it is possible for agents to change their opinion about technology development. After reviewing the history and development of agent-based models briefly in Section 2, the stochastic master functions are developed in Section 3. Then, three core features for agent dynamics are derived. Details for computer simulation are given in Section 5. Next, an empirical analysis based on this model will be exemplified by using various data. Finally, the contribution and implication of this approach are presented and conclusions drawn.

2. Literature review

2.1. Agent model

With the growing number of complex systems in almost every field, it has become the center of interest how to analyze their behavior. Although previous methods have made attempts to derive macroscopic behavior from microscopic properties, most of

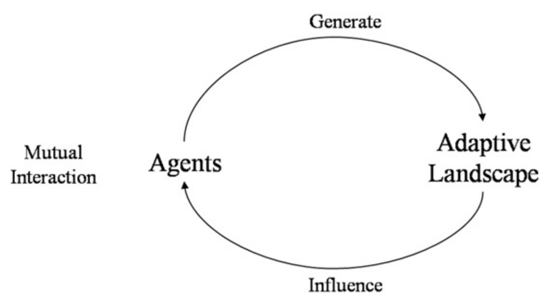

Fig. 1. Nonlinear feedback of Brownian models.

these methods demonstrated that the behavior of complex systems cannot be inferred from their components [14]. Due to nonlinear collective interactions between components, unexpected new behavior has been observed on the macroscopic level. An earlier form of the cellular automata model, traced back to John von Neumann [15], opens the challenge to this problem. However, a major advancement both in concept and model was initiated by Haken [16]. He presented synergetics, a circular causation model between system components and order parameters. Dynamics of interaction between system components generate collective variables, called order parameters, which guide the transition of the overall system to an ordered state. Subsequently, these variables enslave component dynamics. At its heart, this insight makes it possible to describe complex systems with few aggregated variables. Despite this considerable reduction, it is noteworthy that the concept should be based on nonlinear bottom–up interactions denoted as self-organization, rather than a top–down hierarchical approach expressed in a set of equations.

As a parallel but more practical effort, computer simulation has increased its share as a research methodology. Massive computing power makes it possible to simulate the interaction and dynamics of system components denoted as agents on the microscopic level. Computer-based agent models have developed faster than expected due to the belief that complex reality can be reproduced in a computer screen. Cellular automaton, a representative approach, has been revisited and applied to various disciplines such as physics [17,18], biology [19,20] and social sciences [21,22]. In most cellular automata models, cells on a grid are characterized by a discrete state variable. Cellular dynamics occurs in discrete time steps, and depend on the states of neighboring cells. Albeit a simplistic and broad application, this model is subject to some serious drawbacks. The discretization in space, time and state variables often has failed for deriving macroscopic dynamics from microscopic interactions. Moreover, the unit of analysis is not the agent but the cell, the space where agents reside. Some people argue that the cellular automata should present itself as a model of agents in continuous time and space.

Simulation software has conformed to these changing demands for investigating the complex interaction of agents. Early software such as Sugarspace [23] was complete in the basic concepts, but of limited use to deal with real complex problems. While keeping the idea of microscopic dynamics between agents, later software gave agents more attributes, and let the agents adapt themselves to changing conditions autonomously. For instance, a software platform named Swarm offers build-in capabilities such as a possible activity library, memory of past events, response mechanism to changing environments, information processing, etc. [24]. Given by the freedom to setup a simulation as complex as possible, there is a trade-off between the most realistic simulation including much microscopic detail and a simple one with a tractable analytical model. The former is comfortable with matching the complexity in a setup but lacks in-depth system dynamic investigation. Quite the opposite, the latter is good at analytical investigations with a risk of omitting some important features.

To get the agent model within a real but tractable range, the concept of mesoscopy has emerged recently. Microscopic specifications of agents are taken into account only enough to explain an observed emergent behavior on the macroscopic scale. With intermediate complexity, numerous quantitative methods can be used to investigate a particular kind of interaction or property more carefully. More to the point, mesoscopy is an optimized way of describing seemingly random but ordered macroscopic behavior while focusing on microscopic properties and interactions to the extent necessary. The Brownian agent approach can be characterized by the above-mentioned concepts, and used to simulate a variety of complex systems, ranging from physical systems to biological and social systems [25–27].

However, compared with dynamic system models, rarely have agent models been used in technology forecasting. Although they have been highlighted recently by some studies [7,28], applications of agent models are found only in some innovation adoption and diffusion studies [29,30]. Regardless of the application scope, most of applications remain at the naïve level, and suffer from not dealing with real complex problems. Thus, it is no wonder that agent models have yet to produce predictions taken seriously by planners and forecasters. Considering the fact that the future of technology should be a typical of complex problems, more refined and sophisticated agent models should be employed and developed to obtain better predictions.

2.2. Brownian agent

As already mentioned, Brownian agents do not just passively respond to external forces, but are capable of performing a certain level of activity such as interaction with the environment or other agents. A set of state variables, $u_i^{(k)}$ where $i = 1,\ldots,N$ denotes the ith agent and k indicates different variables, is used to describe both activities [27]. The space coordinate denoted as $u_i^{(1)} = r_i$ is one of the important external variables. Expressed mostly in a form of a two-dimensional vector, it specifies the small region where the agents are, and evokes the reaction of them. However, some variables cannot be addressed directly from observable actions, but just inferred indirectly. For instance, the internal energy depot, $u_i^{(2)} = e_i$, makes it possible that agents can consider a variety of actions such as active motion, communication with other agents and environmental changes. The causal relationship seems to be obvious, but cannot be drawn easily from seemingly unrelated actions. By adding the internal state variable of agents, $u_i^{(3)} = \theta_i$, describing the value of certain attributes or different responses to information or environmental conditions, these variables are called internal degrees of freedom. The above-mentioned three variables are crucial to building Brownian agent models, and are frequently found in previous studies. Surely, on the condition that microscopic complexity is under control, more variables can be added.

Any variable can change over time due to either external impact or internal dynamics. When a number of influences are imposed on an individual agent, it is not easy to express the causality in a general way. Langevin [31] tackled this problem and suggested an idea of summing up all of stochastic forces with statistical properties. Exploiting his idea in a similar manner, Schweitzer [27] integrated influences that might exist on a microscopic level but are not observable in a stochastic term F_i^{stoch}. All of

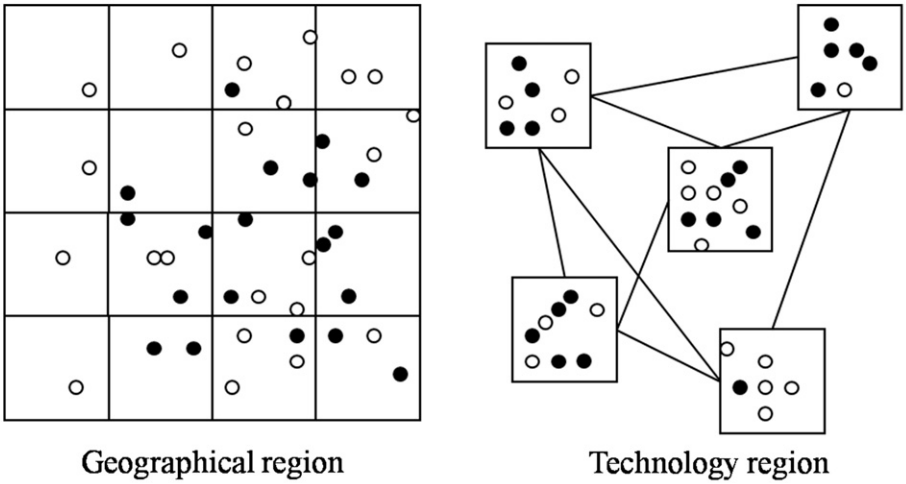

Fig. 2. Geographical region and technology region.

influences directly specified from observables actions are also summed up in a deterministic term $f_i^{(k)}$. Placing these two integrated terms on the right-hand side of the equation, the basic dynamics equation of Brownian agents can be formulated as follows.

$$\frac{\partial u_i^{(k)}}{\partial t} = f_i^{(k)} + F_i^{stoch} \tag{1}$$

Without taking too much microscopic detail into account, researchers can concentrate on particular aspects of a complex system with the integrated stochastic term. The deterministic term usually covers influences by nonlinear interactions among agents and external forces. However, there can be agent-independent working factors, named eigen-dynamics of the system. Some cyclic effects such as seasonality are good examples of working factors. If present, they should be also included in the above formula. Some people have tried deriving the integrated expression of deterministic influences inspired by the idea of a generalized potential landscape, as is created by all possible variables. However, this concept is valid only for gradient systems where $\partial f_i / \partial u_j = \partial f_j / \partial u_i$ holds. Rarely is this requirement fulfilled in high-dimensional systems. Schwetizer [27] eased this strict condition and developed a more flexible idea of an adaptive landscape. Every action of agents changes the state of the adaptive landscape through the channel given by model equations. Subsequently, changes in landscape might affect the actions of agents. Nonlinear feedback process occurs not only among agents, but between agents and the landscape. Taken together, the conceptual process of Brownian models can be described as follows.

3. Basic model equation

Our model is essentially based on the works of Arthur [32] and Schweitzer [11]. The conceptual process and core features are similar but modified to reflect the nature of technology. What differs the most might be the definition of the space. Previous studies usually assumed geographical regions as a collection of boxes on a grid. Within the outer boundary, Brownian motion of an agent is continuous. A single technology region, representing a certain technology, can be defined to be similar to the geographical region. However, the inter-regional relationship is essentially discontinuous as shown in Fig. 2. In terms of the motion of agents, if an agent leaves a region, it will arrive to another region without time consumption via channels between regions.

Narrowly focusing on a single technology region $\mathrm{TR_k}$, where $k = 1,\ldots,n$, it is assumed that $\mathrm{TR_k}$ should be a continuous two-dimensional space with n technology development agents. Agents aim to develop an identical technology forced by the region with slight variation, and are characterized by two variables. One is the current location of an agent given by the space coordinate r_i, which is classified into the external influence variable. The other is an internal state variable θ_i, which can be either zero or one: θ_i {0,1}. Agents with $\theta_i = 1$ are willing to develop the technology, while those with $\theta_i = 0$ are not. When $C_1(t)$ denotes the number of agents with $\theta_i = 1$ at a certain time t and $C_0(t)$ with $\theta_i = 0$, we can obtain the spatiotemporal density of the two agent types in any technology region $\mathrm{TR_k}$ as follows.

$$m_k(r,t) = \frac{1}{TR_k.\text{area}} C_1(r,t)$$

$$n_k(r,t) = \frac{1}{TR_k.\text{area}} C_0(r,t) \tag{2}$$

At a certain rate k^-, an agent with $\theta_i = 1$ can change his decision to not develop technology any more, and become an agent with $\theta_i = 0$. However, persuaded by other agents or motivated by any reason, reverse change can occur at a rate k^+. These actions can be expressed as follows.

$$C_0 \xrightarrow{k^+} C_1$$
$$C_0 \xleftarrow{k^-} C_1 \tag{3}$$

It is reasonable to assume that agents with $\theta_i = 1$ should be immobile. Were it not for decision changes, they will continue to develop a current technology without movement. Still, some agents with $\theta_i = 0$ can move, and migrate to another technology region with attractive alternatives. Taking the concept of a Brownian agent into consideration, it is most likely that agents motion should depend both on deterministic forces and stochastic forces. Within a stochastic approach, the movement can be generally described by following the overdamped Langevin equation.

$$\frac{dr_i}{dt} = f(r_i) + \sqrt{2D}\xi_i(t) \tag{4}$$

The first term, $f(r_i)$, describes the local deterministic force. It should be noted that agents are subject both to local forces and global forces. Some agents can freely access knowledge about other technologies that may be distant from his expertise, and are willing to jump to a distant technology region to generate a new technology. In that case, due consideration should be given to long-range forces guiding that movement. However, the working mechanism of global forces has not been clarified, and is still under hot debate. That is why we put global forces aside in our simulation. In the above equation, it is assumed that technology agents count on information in the local vicinity, and respond only to local forces. The second term sums up all of the random influences. Brownian motion of agents will vary according to the balance of power between two terms. The movement of an agent is predictable if the deterministic force is larger, but random if smaller. Provided that total number of agents is constant, the change in local density over time can be described with the simple reaction-diffusion equation as follows. The subscript denoting the technology region is omitted for convenience.

$$\frac{\partial}{\partial t}m(r,t) = k^+ n(r,t) - k^- m(r,t)$$
$$\frac{\partial}{\partial t}n(r,t) = -\frac{\partial}{\partial r}f(r,t)n(r,t) + D_n\frac{\partial^2}{\partial r^2}n(r,t) - k^+ n(r,t) + k^- m(r,t) \tag{5}$$

The local density of agents with $\theta_i = 1$ can be changed by local opinion change positively at k^+ and negatively at k^-. This is a simple reaction equation. Arguably, the change of local density with agents $\theta_i = 0$ has a more complex mechanism. As for the lower formula of Eq. (5), besides influence of local opinion change in the third and fourth terms, two more influences have to be considered. The first term describes the change of local density due to movement of agents driven by the deterministic force, $f(r,t)$. Located within a technology region overcrowded by so many agents, agents characterized by weak technological competitiveness migrate to other regions in terms of a diffusion process. However, it should be noted that most agents would stay due to a variety of reasons such as invested capital in the present technology, risk-averse character, etc. With the diffusion coefficient, D_n, those movements are captured in the second term. Thus, the derived reaction-diffusion equation is more sophisticated than the upper formula of Eq. (5). Although a pair of basic agent dynamics equations is given, more features comprising k^+, k^- and $f(r,t)$have to be specified for application in technology forecasting data.

4. Core feature specification

4.1. Deterministic force

Despite invested resources and established technological capability, some technology agents decide to withdraw from the current technology market, and search for other opportunities. Even in a current technology region, they can choose to develop another technology variant for the future value. In terms of our model, the deterministic force, $f(r,t)$, acts on agents as an attractive force to another location. Still with $\theta_i = 0$, agents continue to move to better opportunities. However, after moving for some time, agents can stop and develop variants within the current region. When agents move out of the regional boundary, they will migrate to another technology region. Putting inter-region movement aside, we will concentrate on specifying the principal cause of intra-region movement, e.g. the deterministic force. Provided that agents are under local information constraints, it is reasonable that they should respond to local gradients in the technology value function. Hence, the guiding force, $f(r,t)$, can be defined as follows.

$$f(r,t) = \frac{\partial}{\partial r}w(r,t) \tag{6}$$

Here, the technology value function, $w(r,t)$, can be obtained to differentiate the technology value production function with respect to the local density of agents. As usual, a number of inputs such as capital, knowledge and infrastructure can be included in the technology value production function. To keep our model parsimonious as possible, it is assumed that the effect of different inputs could be integrated into a variable, including the number of technology agents. The number of technology agents is correlated positively with most inputs, and could be a good single proxy variable. The basic form of the technology value production function, $v(r,t)$, could be given as follows.

$$v(r,t) = A(r,t)g(r,t) \tag{7}$$

$A(r,t)$ is a pre-factor function representing the level of productivity. It can be divided into two terms, A_c and A_u. A_c reflects the value increase of technology due to physical resources such as capital. Under the assumption that agents should be identical, A_c can be given as constant. The second term, A_u, represents the interaction effects. Actually, technology agents can share their information or knowledge with adjacent agents, and further cooperate or make alliances to maximize technology value production. The more interaction an agent has, the more knowledge it can receive and create. All of these interaction effects, which lead to knowledge accumulation, are captured in the second term. Of particular importance is the fact that all interaction effects should be nonlinear with respect to the local density of agents with $\theta_i = 1$. Thus, A_u is defined to be a nonlinear function of $m(r,t)$. If $m(r,t)$ is low, the synergetic effects resulting from interaction will be low, too. To the contrary, it is no wonder that the mutual positive effect should be increasing as local density of agents with $\theta_i = 1$ increases. However, it should be noted that interaction advantages could be outweighed by disadvantages such as crowding out effects beyond the saturation point. Taking these considerations together, the following assumption can be made.

$$A_u[m(r,t)] \propto exp\{i[m(r,t)]\} \tag{8}$$

Here, $i[m(r,t)]$ works as a shape parameter of the exponential function. As $m(r,t)$ increases, the interaction effects will show a non-linear upward movement. Thus, $i(m)$ can be described to be the utility function in powers of m as follows.

$$i(m) = a_0 + a_1 m + a_2 m^2 + \dots \tag{9}$$

Taking the size of the effects into consideration, the series after the second order can be ignored, and truncated. The balance between positive and negative effects can vary across different technologies. If the positive interaction effect is an ever-increasing function of m, all coefficients a_0, a_1 and $a_2 > 0$ are assumed. When positive effects are overshadowed by negative effects due to saturation, the coefficient $a_2 < 0$ should be assumed with $a_0 > 0$ and $a_1 > 0$. Although A_c is not specified, it is possible to simplify the expression without restrictions of the generality.

$$\overline{A} = A_c + exp(a_0) \approx 2A_c \tag{10}$$

Returning to the Eq. (7), the technology value production function, $g(r,t)$, can be assumed to be a modified Cobb-Douglas production function because we consider only one input variable, and the number of technology agents is analogous to the labor variable in microeconomics. With an exponent β varying across technology regions, $g(r,t)$ can be given as follows.

$$g(r,t) = m^{\beta}(r,t) \tag{11}$$

In Eq. (11), $m(r,t)$ is the local density of agents with $\theta_i = 1$. The exponent β describes the returns relative to the scale of technology value production. With $\beta > 1$, an increasing number of agents will lead to higher average technology value production. On the other hand, decreasing returns to scale can be observed due to crowding-out effects or shortage of resources. In that case, β should be between 0 and 1. β will not vary sharply in similar technologies but will vary markedly between different technologies. By placing two specified terms, $A(r,t)$ and $g(r,t)$, together, the technology value production function, $v[m(r,t)]$ can be defined as follows.

$$v[m(r,t)] = \frac{\overline{A}}{2}\left[1 + exp\left(a_1 m + a_2 m^2\right)\right]m^{\beta} \tag{12}$$

Once production function is determined, simply by differentiating with respect to m, we can obtain the technology value function, $w[m(r,t)]$ in Eq. (13).

$$w[m(r,t)] = \frac{\overline{A}}{2}\left[1 + exp\left(a_1 m + a_2 m^2\right)\right]\beta m^{\beta-1} + \frac{\overline{A}}{2} exp\left(a_1 m + a_2 m^2\right)(a_1 + 2a_2 m)m^{\beta} \tag{13}$$

The deterministic force, $f(r,t)$, is the derivative of the technology value function $w[m(r,t)]$ with respect to the local coordinate r, $\partial w/\partial r$. However, to derive the deterministic force, we should fix the timescale problem in advance. For the timescale of overall dynamics, two different timescales, one for local opinion change and the other for inter-region movement, work simultaneously. On the premise that agents actively search for a better opportunity, the inter-regional movement is more important than local opinion change. This implies explicitly that the timescale of inter-regional movement should be more determining. In other words, the spatial distribution of agents with $\theta_i=1$ can be assumed to be in quasi-stationary equilibrium compared with that of agents with $\theta_i=0$. Then,

$$\frac{\partial}{\partial t}m(r,t)=0 \quad \rightarrow \quad m^{stat}(r,t)=\frac{k^+}{k^-}n(r,t) \tag{14}$$

Hence, the deterministic force, $f(r,t)$, can be determined by multiplying out the derivative, $\partial w/\partial r$ as follows by applying Eq. (14).

$$\frac{\partial w(r,t)}{\partial r}=\frac{\delta w[m(r,t)]}{\delta m}\frac{\partial m(r,t)}{\partial r}=\frac{\delta w[m(r,t)]}{\delta m}\frac{k^+}{k^-}n(r,t) \tag{15}$$

Finally, we can determine k^+ and k^-.

4.2. Local opinion change

Once the technology value production function is determined, deriving the rate of local opinion change boils down to the comparison of the marginal technology value $\partial v/\partial m$ with the local average technology value denoted as w' in Eq. (16). In other words, agents with $\theta_i=0$ will change their opinion on the condition that a current opportunity seems better than any other around them. This notion can be expressed as follows.

$$\frac{\delta v[m(r,t)]}{\delta m}>w' \tag{16}$$

Then, the transition rate k^+ can be defined as follows.

$$k^+=\eta exp\left\{\frac{\delta v[m(r,t)]}{\delta m}-w'\right\} \tag{17}$$

In Eq. (17), the coefficient η determines the timescale of transitions. While the marginal technology value is larger than the local average technology value, the deterministic transition rate, k^+, is larger than the rate of random opinion change, represented by η. If not, the local opinion change rate, k^+, will tend to be zero. The rate of reverse opinion change, k^-, can be simply placed opposite to k^+. With everyone rushing to develop current technology, the marginal technology value falls below the local average technology value, and resulting in reverse opinion change. However, there is a different aspect to consider. Similar to the response of agents with $\theta_i=0$ to local gradients in technology value, agents with $\theta_i=1$ can count on the same information, withdraw from current technology development, and move to another technology opportunity. Thus, it is more reasonable to add the parameter, $b\partial w/\partial r$.

$$k^-=\eta exp\left(-\left\{\frac{\delta v[m(r,t)]}{\delta m}-w'\right\}+b\frac{\partial w(r)}{\partial r}\right) \tag{18}$$

With $b>0$, a higher technology value in other local gradients will accelerate the reverse transition of the local opinion. However, if $b=0$, internal motivation of opinion change should be neglected. In that case, reverse opinion change depends simply on external factors. When technology lifecycle is at the growing stage, agents with $\theta_i=0$ are relatively few. Nevertheless, inter-regional movement is observed frequently due to the proactive character of agents. In that regard, if not dealing in mature industries, it is reasonable to choose $b>0$.

5. Movement of agents

5.1. Intra-region movement

As addressed earlier, intra-region movement of agents depends both on a deterministic force and stochastic random force. What is important is how to define the unit area of a technology value field. Assuming that it matches a technology region as a whole, all agents with $\theta_i=0$ will show similar movement due to the fact that deterministic force should be identical within a region. Only the stochastic force will make some difference. This implies implicitly that agents have complete information about technology value in a region. However, this notion of complete information symmetry is too strong to be imposed. Adopting the view of bounded rationality that agents should count simply on local information, we divided a technology region into a collection of small grids with a unit length, Δs. Then, the local density of agents with $\theta_i=1$ in the ith grid can be defined as follows.

$$m_i(r,t)=\frac{1}{(\Delta s)^2} \tag{19}$$

By response, the deterministic force in the ith grid, $f_i(r,t)$, can be defined, and is different from the deterministic forces in other grids. Then, intra-region movement of agents meets the assumption of bounded rationality on agents, and varies across grids.

Another key specification is the division of movement. The intra-movement of agents in two-dimensional space has to be addressed separately along an axis. We can elaborate Eq. (4) for position *x* as follows.

$$x_i(t+\Delta t) = x_i(t) + \frac{\partial}{\partial x} w_i(x,y,t)\Delta t + \sqrt{2D_n \Delta t}\text{GRND} \tag{20}$$

After a discrete time, Δ*t*, ith agent will move as expressed in Eq. (20) for position *x*. The equation for position *y* reads accordingly. The third term on the right side of the equation. indicates the sum of the stochastic force, represented by Gaussian random number, GRND, with zero as the mean and one standard deviation. Substituting the deterministic force, $\partial w_i(x,y,t) / \partial x \Delta t$, with the function of local density for agents with $\theta_i = 1$, $m(r,t)$, we can derive Eq. (21) in full detail for *x* position.

$$\begin{aligned} x_i(t+\Delta t) = x_i(t) + \Big\{ & \frac{A}{2}\Big[1 + exp\Big(a_1 m_i(t) + a_2 m_i(t)^2\Big)\Big]\beta(\beta-1) m_i(t)^{\beta-2} + \frac{A}{2}\Big[1 + exp\Big(a_1 m_i(t) + a_2 m_i(t)^2\Big)\Big] \\ & \times (a_1 + 2a_2 m_i(t))\beta m_i(t)^{\beta-1} + \frac{A}{2} exp\Big(a_1 m_i(t) + a_2 m_i(t)^2\Big)(a_1\beta + 2a_2(\beta+1) m_i(t)) m_i(t)^{\beta-1} \\ & + \frac{A}{2} exp\Big(a_1 m_i(t) + a_2 m_i(t)^2\Big)(a_1 + 2a_2 m_i(t))^2 m_i(t)^{\beta}\Big\} \times \frac{k^+}{k^-} n_i(x,t)\Delta t + \sqrt{2D_n \Delta t}\text{GRND} \end{aligned} \tag{21}$$

5.2. Inter-region movement

A single technology region is a typical two-dimensional space, and has the same continuous shape with a geographical region. However, this grid form cannot be used to describe the overall structure and position of N different technology regions. Thus, we assume that technology regions require a network form connected via channels as shown in Fig. 2. It should be noted that inter-region distances are given, but region coordinates are not. If coordinates are imposed, inter-region movement of agents is forced to be continuous. Furthermore, it is difficult to distinguish technology regions based on coordinates, and define the adjacency between regions. Our model is free from these problems. More to the point, once a decision to migrate is made by agents, migration to another technology region will take no time, as is reflected in the assumption of inter-region discontinuous movement.

When an agent moves out of the current region, it can move to adjacent regions via channels. Without any channel, agents are compelled to remain in the current region. If only a single channel is connected, agents have no choice but to be carried by that channel. Ambiguous is the case of multiple channels. From the agents' viewpoint, the criteria of the most appropriate channel to expand technology regions are the most important. Seeking the best opportunity possible, agents are willing to move to the region with the highest technology value. Another key factor is distance. The longer the inter-region distance is, the more difficult the movement is. In other words, it is easier to develop a similar technology rather than a totally different technology. Facing up to the obvious trade-off between two factors, agents try to take an optimized behavior. Two criteria of inter-region movement can be expressed as the following ratio indicator.

$$VR_{ij} = \frac{\left(w_j - w_i\right)}{D_{ij}} \tag{22}$$

Given that w_j denotes the technology value of the jth technology region, the numerator indicates the gap of technology value between technology regions. The denominator, D_{ij} is the distance between those regions. If completely rational, agents will choose the channel with maximum VR_{ij} with out exception. There is a strong possibility that all of agents should make the best decision as possible as they can. However, it has been frequently observed that seemingly irrational decisions were made. In that regard, it is better to take a probabilistic approach. Summing up all of VR_{ij} across available channels, we normalized the value of each VR_{ij}. Then, VR_i becomes the probability of choosing the corresponding channel. If the available channels are represented by $w_j - w_i < 0$, agents will stay in the current region.

6. Empirical analysis: Korea's software industry

6.1. Data

Little attention was paid to Korea's software industry in the 1990s due to the narrowly focused ICT development centered on electronics hardware. However, there is a perception that software should be the next generation growth engine. Software accounts for 33.5% production cost on average over a wide array of industries including telecommunication, automobile and medical. Furthermore, it is crucial to technology fusion and convergence, often between unexpected areas. With little available time-series data at an early stage of development, uncertainty is central to Korea's software industry. Thus, a suitable tool to forecast the development path is required. Arguably under these conditions, our method will work better than traditional approaches such as Delphi and extrapolation.

Another concern is the year selection. Assuming that there are no new entrants in a technology region, it is required that the number of technology agents, mostly firms, should be stable. Based on '2004 annual report on Korea's software industry' [33], the sizzling increase of software firms soared up to 75.9% in 1998, but remained around 1% after 2001. With due regard to the data

Table 1
14 software technology regions.

Cluster	Number	Technology region
Package software	1	System software: operation, utility, communication, system management, middleware, etc.
	2	Development and embedded software
	3	Application software: office, science and industry
	4	SI (system integration)
Computer service	5	SI support and maintenance
	6	Data processing
	7	Security: coded data generation, cryptography, etc.
	8	Game
	9	Image and animation
Digital contents	10	Web information
	11	Music
	12	Electronic publication
	13	E-learning
Database	14	Database architecture and search

availability for estimation of other parameters, we fixed the forecasting point as 2004. To determine the number of agents and their initial states, we relied mostly on the '2004 Korea's software firms report' [34]. Additionally, NBER patent citation data were used to estimate the distance between technology regions.

6.2. Initial configuration of technology regions and agents

Each technology region represents a specific technology, meaning that an appropriate software technology classification needs to define technology regions. With reference to the classifications proposed by the Korea Software Industry Association and OECD [35,36], we analyze 14 technology regions as shown in Table 1. Noticeably, some regions show stronger technology proximity, and are grouped as four clusters, which will help us identify the concentration of agents at a more macroscopic level. Moreover, it is clear whether agents are attracted more strongly by intra-cluster concentration force rather than inter-cluster forces.

For inter-region movement of agents, care should be taken to set the distance between regions. Agents moving out of their previous regions are strongly directed to closer regions with greater expected benefits than others. Hence, the absolute value of distance can be set arbitrarily, but the relative value should be estimated based on real-world data. We use the number of patent citations as a proxy measure for technological knowledge proximity. Put simply, the more patent citations there are between technologies, the closer they are. Taking the inverse of the number of patent citations, we obtain the distance, and normalize it between 0 and 100. Normalized distances between 14 software technology regions are shown in Table 2. USPTO software-related patent data granted to Korean Assignees between 2001 and 2003 were collected and used to count the number of patent citations between regions. Due to the fact that USPTO technology classification is not consistent with our software technology regions, IPC (International Patent Classification) codes of ICT patents proposed by OECD were referred to choose software patents only, and then assign them to the above-mentioned 14 regions [37].

The movement of agents is dependent principally on how many agents are located initially at each region. So far, Korea's software technology development has been led by business R&D. As a decision unit of R&D as well as future technology direction, firms will make the right match for our notion of technology agents. However, their impact on technology regions varies according to their strength of market presence and R&D capability. Assuming that a firm with annual sales below 200 million won is regarded as an agent, we assign more agents to a firm in proportion to their sales amount. Put simply, a firm with two billion in sales corresponds to ten agents showing homogeneous movement in the same region. The diversification effect is also noteworthy.

Table 2
Normalized distances between 14 software technology regions.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0.00	0.02	0.85	0.09	0.35	0.70	0.10	20.00	11.10	3.12	12.50	11.11	9.09	0.06
2	0.24	0.00	0.21	0.19	0.03	1.55	0.12	25.00	12.35	5.27	11.20	33.33	11.20	0.46
3	1.25	1.10	0.00	0.92	0.85	0.65	1.64	5.52	2.10	2.05	2.10	1.55	1.33	1.10
4	0.08	0.26	0.91	0.00	0.04	1.25	3.85	9.91	1.80	2.55	50.00	33.33	9.09	0.54
5	0.12	0.37	0.60	0.06	0.00	0.90	5.56	7.14	1.10	1.47	50.00	33.33	33.33	0.81
6	0.82	1.25	1.10	1.50	1.47	0.00	0.81	6.12	0.60	0.27	11.11	33.33	9.12	0.32
7	0.04	0.25	1.67	3.23	6.67	0.79	0.00	2.27	33.33	0.27	33.33	50.00	11.11	0.21
8	5.38	5.56	4.76	9.09	4.55	5.43	95.00	0.00	0.12	4.00	2.35	50.00	33.33	3.85
9	3.50	4.20	0.75	2.80	1.15	0.84	50.00	11.11	0.00	0.24	11.20	5.51	8.91	0.23
10	1.23	5.78	1.19	0.32	0.63	0.47	0.37	9.09	0.26	0.00	6.67	2.25	3.11	0.08
11	100.00	33.33	8.33	14.29	8.33	20.00	9.09	5.32	50.00	8.93	0.00	11.11	12.50	4.41
12	50.00	50.00	9.11	7.23	7.14	12.50	14.29	32.15	11.11	3.03	10.25	0.00	6.67	5.23
13	50.00	12.50	7.69	5.12	4.78	3.23	25.00	11.84	50.00	2.70	8.02	20.00	0.00	5.51
14	0.04	0.12	0.26	0.85	1.08	0.64	0.97	7.69	0.39	0.14	6.67	5.88	4.76	0.00

Table 3
Total and internal state-wise number of agents in 14 software technology regions.

State	Technology region													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
$\theta_i=0$	56	31	372	816	230	7	22	62	3	18	31	3	2	5
$\theta_i=1$	450	175	790	3985	2323	132	47	233	49	95	110	10	85	103
Total	506	205	1162	4801	2553	139	70	295	52	112	142	13	87	108

Actually, larger firms tend to diversify their technology portfolio, and thus be positioned to several regions simultaneously. To avoid the problem of overlapping agents, the number of agents allocated to each region is determined by the average product sales ratio over 14 technology regions. For instance, in the case of a firm with one billion sales composed of half in software packages and the rest in database sales, half of the ten agents are allocated to each region.

Another important factor is the initial internal state of whether firms are willing to continue their technology development in the current areas or not. First, we examine official announcements of firms between 2003 and 2004, and assign an internal state of zero to firms implying either refocusing of technology direction or abandoning the current technology. Then, financial statement and R&D expenditure are examined to choose firms with a sudden decrease of product sales or R&D activity in current areas, and a zero state was assigned to them. The most ambiguous are small and medium size firm with up to 15% of total firms but 5% of overall industry sales. The '2004 Korea's software firms report' [34], '2004 annual report on Korea's software industry' [33] and a great number of official homepages of software firms are used, and result in Table 3.

The final factor of density is the area of each technology region. The wider the area is, the lower the resulting density. At the same time, fewer agents move out of regions with lower density. With due consideration to these contradicting effects, care should be taken to fix the areas. We assume that the area of each technology region should reflect the potential exploitable benefits. The smaller an area is, the less the potential benefits it contains, which implies that small areas reach the highest technology value earlier, but also struggle from the saturation effect. However, in a large region with few agents, the low density of agents will lead to low technology value, and leave vast benefits unexploited. We depend on expert judgments to estimate the area of a technology region based on domestic market growth expectation. The results in Table 4 were reviewed and checked by two researchers and two industry experts in each cluster. With the remaining parameters, first, it is assumed that both synergetic interaction and saturation effect work together in the technology value production function, but the latter is modestly weaker. Hence, four parameters are determined to be $A=2$, $a_1=0.06$, $a_2=-0.02$ and $\beta=0.7$. Then, the diffusion coefficient, D_{n}, is set to 0.01 to adapt the mean spatial displacement of agents to the area of each region properly, and make the movement of agents neither fast nor slow. The minimum technology value,w', is set to 1.4, while $\eta=0.2$, $b=0.5$ and $\Delta s=2$.

6.3. Results

With the configuration specified above, computer simulation was carried out. Fig. 3 presents the snapshot comparison of the overall picture between the initial state ($t=0$) and stabilized state ($t=1000$). As expected, it is clear that economic motivation of technology agents should make them concentrate on some regions. Noticeably, TR2 (development software), TR7 (security), TR9 (image and animation) and TR12 (electronic publication) recorded an increase of agent density with $\theta_i=1$, meaning that a number of agents are directed to those regions with more benefits. However, some regions are consistently stable with little fluctuation. The largest regions such as TR4 (SI) and TR5 (SI support and maintenance) are remarkably stable, showing almost no change in the density of agents with $\theta_i=1$ while those with $\theta_i=0$ actively migrate to other regions. Moreover, the overall density of agents with $\theta_i=1$ does not reach a fixed stationary value, but fluctuates within a very small range between 97.2% and 97. 8%. This implies that there is fluctuation of internal states and inter-region movements in some regions, meaning that the dynamics of agent density does not converge into a stationary state. Although it is not fixed, the range of the density is sufficiently narrow that it should reach a quasi-stationary state.

Tracing the evolution of the local agent densities over 14 technology regions, we observe three stages. During the first stage for $t<100$, many agents with $\theta_i=0$ escape their current regions, and reposition themselves in other regions. Steep increases in the density of agents with $\theta_i=0$ within some regions in Fig. 4 are mainly due to this movement. However, Fig. 5 shows that the local density of agents with $\theta_i=1$ increases modestly at best, meaning that many agents rush to escape and migrate, but have not determined to settle themselves in new regions. For instance, the density of agents with $\theta_i=0$ in TR2 (development software) increases by 30% compared with that of $\theta_i=1$ that merely increased by 6%. One thing to note is that the early mass escape of agents

Table 4
Initial density and area of 14 software technology regions.

Measure	Technology region													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Density ($\theta_i=0$)	0.05	0.05	0.23	0.15	0.01	0.02	0.09	0.13	0.01	0.02	0.14	0.05	0.01	0.01
Density ($\theta_i=1$)	0.39	0.28	0.49	0.71	0.76	0.33	0.18	0.48	0.22	0.11	0.48	0.16	0.21	0.21
Area	34^2	25^2	40^2	75^2	55^2	20^2	16^2	22^2	15^2	30^2	13^2	8^2	20^2	22^2

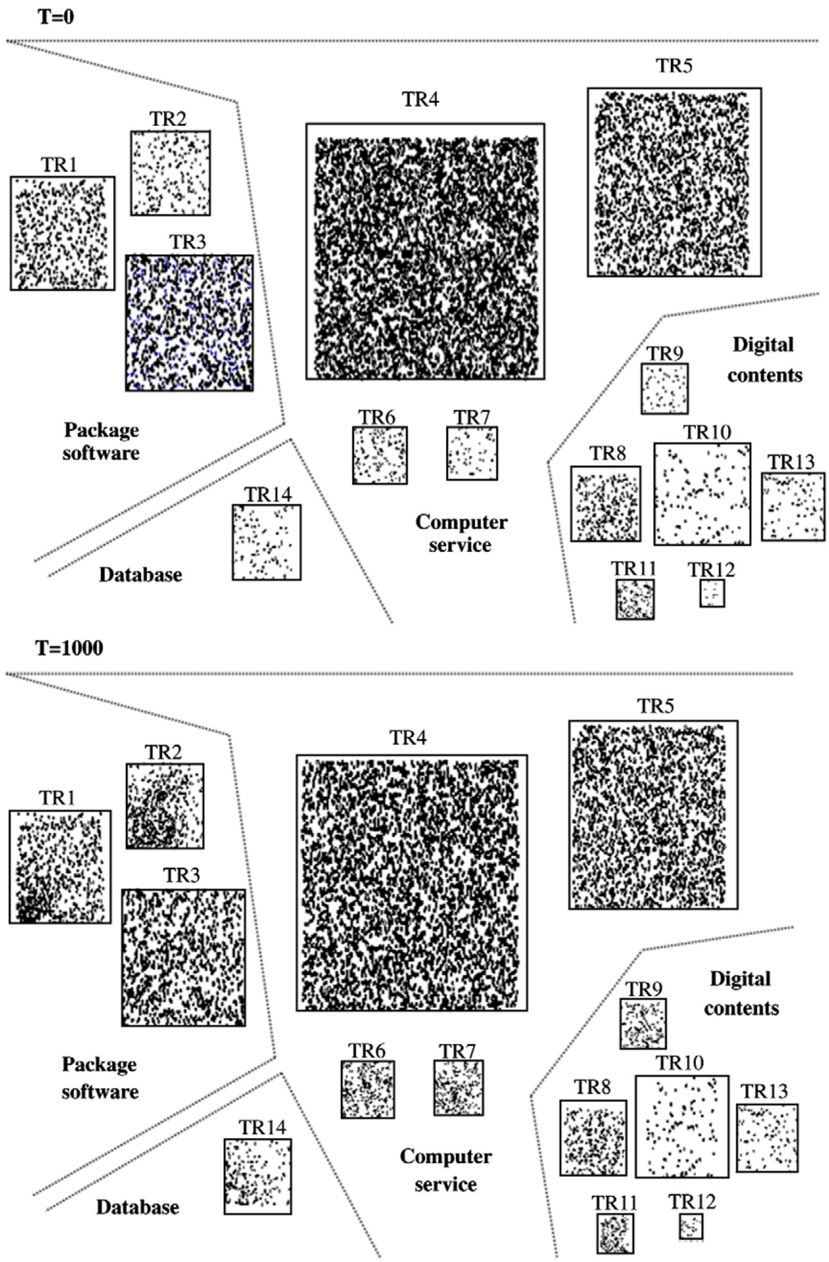

Fig. 3. Agents in 14 technology regions for different times, $t=0$ and $t=1000$.

with $\theta_i=0$ should lead to a stabilized state. TR3, TR8 and TR11 are typical of those regions showing both a sharp decrease in the density of agents with $\theta_i=0$ beyond 75% and a slight increase in agent density with $\theta_i=1$, on average 3%, even in the later stages.

The second stage for $100<t<700$ is characterized by steady but focused concentration of agents over some regions. It is noteworthy that the overall density of agents with $\theta_i=0$ decreases drastically from 12.7% to 2.4%, meaning that most agents are determined to stay in their current regions, and work on technology development. However, increases in the density of agents with $\theta_i=1$ are severely uneven. Agents are directed to regions with higher technology value and shorter inter-regional distance, resulting in high growth regions with the density of agents with $\theta_i=1$ running three times more than those in other regions. TR2, TR6, TR7, TR9, TR12 and TR14 belong to this category. Fig. 5 makes it clear where the concentration of agents occurs. In the third stage after $t>700$, the local and overall density of agents both with $\theta_i=0$ and $\theta_i=1$ continue to fluctuate within a small range below 1%. Hence, there is little difference in density between the ends of the second and third stages.

The inter-region movement of agents gets much clearer with the cluster-wise change of both densities shown in Table 5. For the first stage, half of the agents with $\theta_i=0$ in the second cluster migrate to other clusters, and play a leading role in the first inter-region movement. The movement is severely lopsided with few migrations to the second cluster. This translates into the fact that

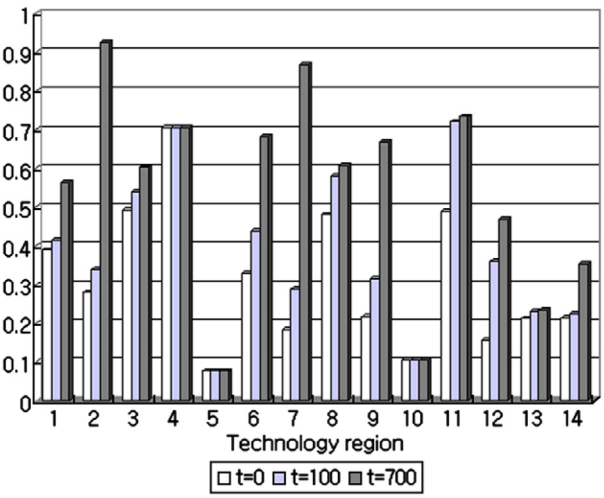

Fig. 4. Changing density of agents with $\theta_i = 1$.

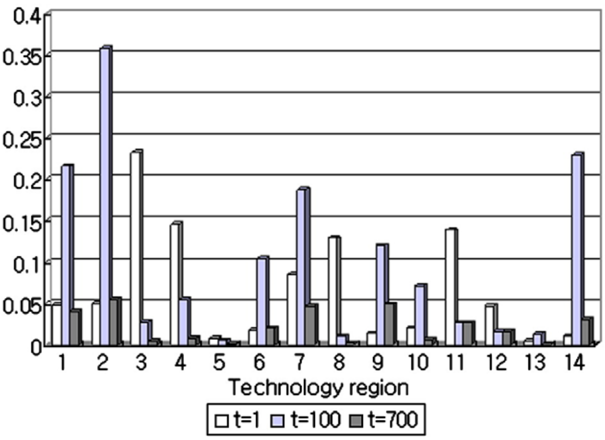

Fig. 5. Changing density of agents with $\theta_i = 0$.

the second cluster, especially the SI technology region, should be regarded as a no-go area for most of agents with $\theta_i = 0$. Actually, the SI industry in Korea has faced domestic market saturation recently, and has had difficulty in finding new sources of further growth. In that regard, our results support the idea that many current firms in the Korea's SI business are willing to make a shift to other technologies. The second stage gives the near-term picture of Korea's software industry. Taking the number of agents and size into consideration, the first cluster will lead the way by a 23% increase of agent density with $\theta_i = 1$. The third cluster amounts to an

Table 5
Cluster-wise discrete change of densities for $0 < t < 1000$.

Time	Density ($\theta_i = 0$)				Density ($\theta_i = 1$)			
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 1	Cluster 2	Cluster 3	Cluster 4
0	0.14	0.12	0.03	0.01	0.42	0.72	0.16	0.21
100	0.16	0.06	0.07	0.20	0.44	0.72	0.17	0.22
200	0.15	0.05	0.05	0.23	0.46	0.73	0.20	0.22
300	0.14	0.05	0.02	0.22	0.49	0.74	0.21	0.24
400	0.11	0.04	0.02	0.16	0.54	0.75	0.22	0.26
500	0.06	0.03	0.01	0.10	0.59	0.75	0.23	0.29
600	0.04	0.02	0.01	0.03	0.62	0.76	0.24	0.34
700	0.03	0.01	0.01	0.03	0.63	0.76	0.24	0.35
800	0.03	0.01	0.01	0.03	0.63	0.76	0.24	0.35
900	0.02	0.01	0.01	0.03	0.64	0.76	0.24	0.35
1000	0.03	0.01	0.01	0.03	0.63	0.76	0.24	0.35

Table 6
Annual software production value over 14 technology regions in 2003 and 2005.

Year	Technology region													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
2003	148	50	240	876	309	12	7	52	15	25	11	2	8	28
2005	164	59	259	875	421	13	10	62	15	57	16	3	8	29
% increase	11	18	8	10	36	2	37	20	−3	128	45	23	5	3

(unit: 10 billion Korean won).
Rearranged from Korea's software industry statistics 2006.

8% increase, but records similar growth rate of 50% compared to the first cluster. However, focusing on the increase due to the inflow of agents from other regions without the effect of local opinion change, the first cluster value of 24% (10/ 42) is much less than the third cluster of 37.5% (6/16). In other words, inter-region movement of agents is directed more to the third cluster. Although the fourth cluster yields the highest growth rate of 70%, its number of agents is less than a fifth of the third cluster, and a tenth of the first. Dominant as SI and IT service industries are in Korea's software industry, more emphasis both by government and business has been given to package software, embedded software and digital contents. Our results suggest explicitly that economic motivation of technology agents should drive them into technology regions thereby increasing the share of those regions.

To validate our forecasting results statistically, time-series data such as patents, sales and R&D expenditure need to be collected. However, due to the fact that our forecasting point is at the end of 2003, only data between 2003 and 2005 were collected. Despite incomplete sampling, annual software production values over 14 technology regions is presented for a rough comparison in Table 6. The overall movement is very similar with what our model simulates, showing that the SI sector is slowing with a slight and modest increase of other industries. Notable differences are observed in the TR5 and TR10 regions. TR10 tops the increasing rate of other regions with a 128% increase in annual sales, while our model expects almost no change. This is mainly due to the upsurge of web-based digital educational contents demands of the public sector. By response, firms seem to increase their production. Sim;ilarly, with the staggering demand in TR4, a temporary alternative to exploit opportunities in TR5 arises, and might result in 36% increase in sales. Taken together, Table 6 makes it clear that there is economic motivation of technology agents for future technology development in play, but our model is vulnerable to temporary noises such as sudden fluctuation of demands.

7. Conclusion

Researchers and managers have been working hard to put right figures on future technology direction and its importance. However, today's innovation process, best characterized by nonlinearity and interaction, makes previous forecasting methods obsolete. Thus, the present methods struggle under a cascade of uncertainties and complexities. Recently, agent-based models have turned out to be good at describing interactive structure formation, and are regarded as promising alternatives. For practical application, it has not been easy due to the fact that neither complex nor simple agent models can match well with reality. Standing somewhere between extremes, a Brownian agent model can be a good solution to delve into a real complex problem and capture its essential mechanism while controlling both complexities and uncertainties at an intermediate level. Adapting such a model to technology development and forecasting, we make it possible for agent-based models to produce new and value-added predictions in practice. To that end, our study also provides valuable information on how to design agents, regions, and their interactions.

With Korea's software industry data, a computer simulation was carried out. Given the binary internal state of whether they develop current technology or not, agents are positioned in their current technology regions. Attracted by more technology value with some fluctuations, agents show continuous intra- and inter-region movement continuously. First, what we find is that the overall dynamics of agents reach a quasi-stationary nonequilibrium state. In other words, only a small fraction of firms continues to abandon current technologies, and switch to other ones. Most firms work on steady technology development. Also noteworthy is the concentration of agents and coexistence of concentrated regions. Apparently, agents migrate to regions with more expected benefits. This results in concentration of agents and increasing density of some major regions. However, the majority of agents cannot concentrate on a single region. Major regions establish their own attraction areas, and thus the coexistence of them becomes stable. Finally, a rough comparison with production data shows that the proposed model should be a fair reflection of the economic motivation of agents, and give good estimates overall.

Nevertheless, only forward prediction can demonstrate the usefulness of this model. If not, at the very least, statistical tests with time-series data, such as economic significance test are needed to validate the performance of this model. Of particular weakness is the fact that it cannot consider the overall industry growth. Without new entrants, the proposed model can only predict the near-term rearrangement of industry focus. In other words, the model should be modified to be applicable for any stage of industry lifecycle. Moreover, new entries into a promising technology region will be accelerated by a set of perceived future-oriented factors such as a forecast of sales, a large-scale governmental support, etc. Those factors need to be reflected in the future study. Another problem is the fact that the unit of time in our model is not defined to be an actual unit of time such as month and year. The match between two units is a must-be condition for forecasting in practice. Also, as the comparison with actual production value data shows, our model is vulnerable to temporary noises such as a sudden explosion of demands. Last but not least, consideration is not given enough to the heterogeneity of agents. Agents are different in terms of heterogeneity, attitude to uncertainty, utility function, etc. The pattern of aggregation and movement of agents can vary a lot.

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