Technological Forecasting & Social Change 106 (2016) 53–64

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

Stochastic technology life cycle analysis using multiple patent indicators

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ARTICLE INFO

Article history:
Received 25 August 2015
Received in revised form 10 January 2016
Accepted 27 January 2016
Available online 1 March 2016

Keywords:
Stochastic technology life cycle analysis
Technology's progression
Hidden Markov model
Multiple patent indicators
Technology intelligence

ABSTRACT

Technology life cycle analysis plays a crucial role in setting up investment-related strategies. The dominant approach to technology life cycle analysis utilizes curve fitting techniques to observe technological performance over time. However, doubts have been expressed about the accuracy and reliability of this method, due to its use of single indicators and the necessity of making assumptions about pre-determined growth curves. As a remedy, we propose a stochastic technology life cycle analysis that uses multiple patent indicators to examine a technology's progression through its life cycle. We define and extract seven time-series patent indicators from the United States Patent and Trademark Office database, and employ a hidden Markov model—which is an unsupervised machine learning technique based on a doubly stochastic process—to estimate the probability of a technology being at a certain stage of its life cycle. Based on this model, this paper also investigates patterns of technology life cycles, future prospects of a technology's progression, and characteristics of patent indicators between technology life cycle stages. The systematic process and quantitative outcomes the proposed approach offers can facilitate responsive and objective technology life cycle analysis. A case of molecular amplification diagnosis technology is presented.

1. Introduction

Technology life cycle analysis has interested decision makers in both industry and government who aim to set up investment-related strategies. Prior literature has revealed that technologies' life cycles generally go through four to six stages in terms of their competitive impact and the integration of their products and/or processes, and that their relative value depends on their life cycle stages (Ernst, 1997; Little, 1981; McCarthy, 2003). While such conceptual frameworks have been widely accepted in academia and practice, how best to use quantitative data and scientific methods to identify a technology's current life cycle stage and its future prospects (Albert et al., 2015; Gao et al., 2013; Haupt et al., 2007) remains major questions for consideration by decision makers.

Modeling and analyzing a technology's progress through its life cycle is a task beset with hazards, such as uncertainty, data unreliability, and the complexity of real world feedback. As such, previous studies have largely relied on expert knowledge (e.g. the use of analogies and Delphi methods). Among others, probably the most scientific approach to technology life cycle analysis is offered by curve fitting techniques that fit growth curves to time-series technology performance indicators and extrapolate those curves beyond the range of the data to obtain estimates of the technology's future prospects (Shin et al., 2013). Several empirical studies have found that S- or double S-shaped evolutions are typical (Achilladelis, 1993; Achilladelis et al., 1990; Andersen, 1999; Ernst, 1997). However, while all these studies have proved quite useful for forecasting either the performance or substitution of technologies, doubts about the method's accuracy and reliability have been cast due to its use of single indicators (Gao et al., 2013; Haupt et al., 2007; Watts and Porter, 1997), and the assumption that growth curves are pre-determined (Lee et al., 2012a, 2012b). Moreover, the interpretation of research results tends to be intuitive and ambiguous, since this method still relies on experts at critical points. For example, one might ask, what is the stage of a technology's progression when the patent application count is 100? Can we say that the technology has transitioned from one stage to another if the patent application count changes to 150? Or is it just a fluctuation in the same stage? The link between patent indicators and technology life cycle stages is still missing.

These drawbacks necessitate the development of a new method to trace the progression of a technology's life cycle, so that such analyses can more adequately inform decision making. Three main issues are key to this problem, and need to be addressed. First, in terms of the idiosyncratic aspects of a technology's progress, a life cycle is specific to an individual technology, and has its own dynamics and rules of evolution (Lee et al., 2012a, 2012b; Shin et al., 2013). The classical bell-shaped curve is the most common pattern, but it is not the only shape. Many different patterns—such as cycle-recycle, rapid penetration, and innovative maturity—have been discovered (Brockhoff, 1967; Cox, 1967; Cunningham, 1969; Kovac and Dague, 1972; Patton, 1959; Polli and Cook, 1969; Rink and Swan, 1979): moreover, these patterns

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http://dx.doi.org/10.1016/j.techfore.2016.01.024
0040-1625/

cannot easily be generalized and applied to new types of technologies (e.g. converging technologies). Hence, previous determinisms based on curve fitting techniques need to be extended to add more flexible approaches to capture the different forms and shapes of technology life cycles. Second, with respect to its intangible aspects, a technology's life cycle cannot be observed directly, so neither the process of its progression through that cycle, nor the stage it has reached, cannot be ascertained fully: all we can observe are some proxy indicators that may or may not be directly linked to a technology's progression. Although a couple of studies have discussed the characteristics of such indicators for technology life cycle analysis (Haupt et al., 2007), there exists little theoretical understanding about, and has been little methodological investigation into, the complex interactions between proxy indicators and the stages of a technology's progression. So these indicators need to be further investigated to estimate the life cycle stages of an object technology, and to facilitate firms' stage-customized decision making. Last—but not least from a practical standpoint—some researchers argue that expert-centric approaches are better methods, since such issues as using single indicators or method complexity are less critical. However, expert-centric approaches need to be supported by good quality and well-organized information, since they can be time-consuming, costly, and inconsistent (Kostoff, 1998; Shibata et al., 2008). In this respect, such methods as the use of analogies[1] and k-nearest neighbors algorithms[2] have been suggested, but are of little help to industrial practitioners since it is almost impossible to obtain the historical information about the evolutionary patterns of similar earlier technologies that such methods require. Thus any approach that is proposed needs to allow for the speedy analysis of a wide range of technologies without the need for supplementary information, so that its results can support decision making by showing the plausible prospects of a technology in the face of future uncertainties at acceptable levels of time and cost.

Considering these issues, we propose a stochastic technology life cycle analysis approach to identifying the stage of a technology's progress through its life cycle using multiple indicators extracted from a large-scale scientific and technical database. We chose patents as a data source for this research because first, almost 80% of technological information can be found in patent publications, which are considered valuable data sources, since they are published according to international standards (Lee et al., 2011); second patents include not only technological but also managerial information, such as countries, assignees, and inventors (Geum et al., 2013); third, patents provide information about technology life cycles before the start of product (Agarwal, 1998; Gort and Klepper, 1982) or industry life cycles (Debackere et al., 2002; McGahan and Silverman, 2001), and so can assist firms in making timely decisions about new businesses; and finally, the scope of the information patents offer is global, and so applicable to a wide range of technologies (Lee et al., 2009).

The tenet of this research is that significant changes of patent indicators can provide valuable information on a technology's progression from one stage to another during its life cycle. To this purpose, we first define and extract seven time-series patent indicators—patent activity, technology developers, technology scope, prior knowledge, technology value, duration of examination processes, and protection coverage. We then employ a hidden Markov model (HMM), which is an unsupervised machine learning technique based on doubly stochastic process (Rabiner and Juang, 1986), to estimate the probability of a technology being at a certain stage of its life cycle. This method models the state sequences that cannot be observed (i.e. technology life cycle stages) based on the observation sequences (i.e. patent indicators) that the hidden states generate. The HMM is of practical use in that it does not need any supplementary information such as pre-determined growth curves and can be fully automated. The approach we propose therefore incorporates the issues noted above into a technology life cycle analysis model, based on which, this paper also investigates technologies' life cycles patterns, their future prospects based on their life cycle progressions, and the characteristics of the patent indicators at their different stages. We also develop a software system to automate our method, allowing even those who are unfamiliar with patent databases and complex models to benefit from our research results.

We applied the proposed approach to support Korean small and medium-sized high-tech companies in conducting technology life cycle analyses at the request of the Korea Institute of Science and Technology Information (KISTI). We adopted the United States Patent and Trademark Office (USPTO) database for this research, since it contains the most representative data for analyzing international technology. Our experience showed that the approach enables diverse technologies to be analyzed swiftly, and provides objective evidence for its results. Moreover, our method enables us to perform systematic and continuous monitoring of the progression of a technology's life cycle, yielding high potential benefits at relatively low cost. The results of our case study also enable us to identify a way to improve the proposed approach, which we expect to be a useful complementary tool to support experts' decision making, especially for small and medium-sized high-tech companies that are considering entering new technology areas, but which have little domain knowledge, and in dynamic industry environments where technology monitoring is indispensable. We believe the systematic process and quantitative outcomes our approach offers can facilitate responsive and objective technology life cycle analysis.

This paper is organized as follows. Section 2 presents the background to our research, and Section 3 explains our research framework, which is then illustrated by a case study of a molecular amplification diagnosis technology in Section 4. Finally, Section 5 gives our conclusions.

2. Background

2.1. Quantitative approaches to technology life cycle analysis

The notion of technology life cycles was first introduced by Little (1981). Since then, most studies on technology life cycle analysis have been based on the firm assumption that a technology (or a group of technologies) has a cycle of four stages—introduction, growth, maturity, and saturation—according to its competitive impact and the integration of its products and/or processes. Following this assumption, early research attempted to figure out an S- or double S-curved technology progression to anticipate the technologies' futures, based on curve fitting techniques using technology performance indicators (Achilladelis et al., 1990; Achilladelis, 1993; Andersen, 1999; Ernst, 1997).

Highlighting possible avenues for methodological adaptation, there have been certain recent shifts in the directions of research on technology life cycle analysis, from curve fitting techniques using single technology performance indicators, to interdisciplinary approaches using multiple indicators. We can summarize the major studies' results as follows: Haupt et al. (2007) identified six patent indicators to detect the changing stages of a technology's progression by examining significant changes in their means; Järvenpää et al. (2011) investigated the characteristics of technology life cycle indicators extracted from different databases including USPTO, Science Citation Index (SCI), Compendex, and LexisNexis; and Hikkerova et al. (2014) identified the two main factors that determine technology life cycles at the individual patent level. There is a consensus among these studies that no single indicator can possibly reflect a technology's progression fully.

[1] This method anticipates the evolution of a technology based on the growth patterns of similar earlier technologies, assuming that the greater the similarity, the more likely the pattern will pertain. However this method is subject to certain limitations that stem from lack of inherent necessity, historical uniqueness, historically conditioned awareness, and casual analogy (Martino, 1993).

[2] This method stores all available cases and classifies new cases based on a similarity measure. However, the values of dependent variables must be known for a sufficiently large part of the data set to apply supervised data mining techniques (Bishop, 2006).