Paper to be presented at the DRUID 2012

on

June 19 to June 21

at

CBS, Copenhagen, Denmark,

Evolution of technological diversity in software: A case study of video indexing

Özaygen Altay
Institut Mines-Télécom, Télécom Ecole de Management
Management, Marketing and Strategy Department
altay.ozaygen@telecom-em.eu

Abstract

In this paper we have analyzed the development of a software technology and its relation to its technological modules through patent connectivity analysis. We have conducted a case study on video indexing which is a technology that automatically classifies and helps to retrieve information from video content. We have analyzed video indexing technology depending on its three main technological modules, namely optical character recognition, audio/speech analysis and image analysis. Four findings emerged: First, with this approach we have identified a vertically integrated firm. Second, we have spotted different development trajectories of software related technologies. Third, we have found that in each analyzed patent group, the most cited patents do not have a technological impact. Fourth, we have identified that firms having an impact on the development of the modules either have high diversity leading to multi-technology firms or have a very small diversity which points to very specialized firms. Consequently, we discuss the evolution of software development through patent analysis. Moreover, we also examine the use of patent connectivity analysis for software related technologies.

Jelcodes:O32,-

Evolution of technological diversity in software: A case study of video indexing

Altay Özaygen

Institut Mines-Télécom, Télécom Ecole de Management

Abstract

In this paper we have analyzed the development of a software technology and its relation to its technological modules through patent connectivity analysis. We have conducted a case study on video indexing which is a technology that automatically classifies and helps to retrieve information from video content. We have analyzed video indexing technology depending on its three main technological modules, namely optical character recognition, audio/speech analysis and image analysis. Four findings emerged: First, with this approach we have identified a vertically integrated firm. Second, we have spotted different development trajectories of software related technologies. Third, we have found that in each analyzed patent group, the most cited patents do not have a technological impact. Fourth, we have identified that firms having an impact on the development of the modules either have high diversity leading to multi-technology firms or have a very small diversity which points to very specialized firms. Consequently, we discuss the evolution of software development through patent analysis. Moreover, we also examine the use of patent connectivity analysis for software related technologies.

Keywords: modularity, software patents, patent analysis, citation network analysis, diversity.

1 Introduction

It is shown that modularity has an effect on intrafirm, interfirm and institutional settings (Garud and Kumaraswamy, 1995; Langlois and Robertson, 1992; Sanchez and Mahoney, 1996). Modularity forces firm managers to know more than what the firm is producing and drives them to ensure that modules are compatible with the modularity of the architecture (Baldwin and Clark, 1997). At the same time, the specialization in the knowledge production, the increasing complexity of the technology and the increasing product level interdependencies also force multi-technology firms to have larger knowledge boundaries than their activity fields. These large knowledge boundaries help firms coordinate suppliers of different technologies for successful system integration (Brusoni et al., 2001).

Concerning modular production, Baldwin and Clark (1997) make a distinction between two different parties. The first one is the architect which is the system integrator. The architect has to attract the module producers by convincing them that the designed architecture is viable. The second one is the module producer which has to master the module production and enter into the market very quickly. After the entry, the module producer has to move into another market or increase the module's performance as the number of agents increase in the market. Langlois and Robertson (1992) describe the early stage of development during which the technology is rapidly changing with a high degree of both technical and market uncertainty. During this early development stage a decentralized production system allows introduction of new entrants. At the same time, rapid prototyping among module producers could be observed. However, during the systemic innovation phase, coordination among different module producers is difficult due to compatibility across components. This difficulty is increased especially if there are some constraints imposed by compatibility requirements (Langlois and Robertson, 1992). At that stage of production, vertical integration has the advantage to coordinate the production of modules and their integration by decreasing the integration cost. However, authors argue that, with a varied consumer demand and flexible manufacturing, modular systems are likely to become important in the future.

There are advantages of a modular product system; Fleming and Sorenson (2003) argue that if a firm has difficulties to release products from R&D to the market due to some technological complexities, the firm could use modular off-the-shelf components and release products that have more mature technology. Moreover, modularly upgradable systems can help firms to reduce product development time, reduce cost and provide customers with continuity (Garud and Kumaraswamy, 1995). Examples given to explain the advantages of modularity, interfirm networking and system integration due to modular production are presented generally for manufacturing products such as stereo systems, micro-computers (Langlois and Robertson, 1992) and computers (Baldwin and Clark, 1997). Moreover, there are important similarities between the above researchers' claims and the concepts set by Parnas (1972) at the dawn of the software engineering.

In this paper, we attempt to answer whether firms having an impact on the development of a software related technology choose to develop all necessary modules in-house and adopt a vertical integration or whether they opt a horizontal integration. In order to understand vertical or horizontal integration that firms might adopt, we also need to investigate the technological diversity of firms having an important technological impact on a certain software technology. To answer these questions, we have taken into account the development of the technology and firms' characteristics. Another objective of this paper is to test the capacity of patent analysis for software related technologies.

As a methodology we have used patent connectivity analysis (Batagelj, 2003; Verspagen, 2007). A patent is an important indicator of novelty which is validated through a patent examination process (Griliches, 1990). Moreover, patents represent the best archive about inventions and cover virtually every field of innovation in most developed countries (Jaffe and Trajtenberg, 2005). The patenting practices in software industry give an important tool to understand and analyze the innovation and intellectual property rights (IPR) procedures in this field.

This research focuses on video indexing as a case. Video indexing technology enables semantic search on the content of a video file. This technology, which stands on advanced computer algorithms, helps to find a pattern, image, sound or text within a video database. The paper continues with a short literature survey on modularity, technological diversity and patent analysis, in section 3, technological development of video indexing and its three main technological modules are described. In section 4 our methodology is presented. Section 5 concludes.

2 Theoretical framework

2.1 Modularity

A modular and non-modular complex system has been illustrated by the two watchmaker named Tempus and Hora by Simon (1962). One became successful by assembling modularly designed watches and the other became bankrupt because of non-decomposable system design. Modularity at its most abstract level is the degree to which a system's components can be separated and recombined (Garud and Kumaraswamy, 1995). A complex system is hierarchical and it is the combination of different parts that have non-trivial interactions. A complex system could be analyzed or created by decomposing it into its subsystems, and recursively its subsystems could also be analyzed in the same way (Simon, 1962). A modular system brings flexibility by increasing the number of possible combinations. Baldwin and Clark (1997) describe a module with its visible and hidden information. The visible portion is the architecture, interfaces and standards that a module contains in order to work consistently within an assembled product. The hidden information of a module is its internal functioning mechanism. One of the advantages of modularity is the possibility to do a multi-site development. The hidden information could be left to be developed by the production site, but, that module should be compatible with the visible portion.

Modular architecture has also an effect on the innovative activities. Modular architecture leads to independent innovation activities to be carried out without the need to change the whole system. On the other hand, change in production affects the firm's organization. Sanchez and Mahoney (1996) argue that firms producing modular products are also urged to switch to the organizational modularity. This fact creates a pressure on the firms to extend their knowledge beyond what is required for their production and forces them to make sure that modules are compatible with the architecture (Baldwin and Clark, 1997). These greater knowledge boundaries help the firm cope with the technological complexity and deal with the product level interdependence. Besides, larger firms knowledge boundaries help firms coordinate suppliers of different modules which comprise different technologies and integrate them (Brusoni et al., 2001).

Modularity is a double-edged sword for incumbent firms. Modularity can contribute to the market success of a product. However, it might also undermine the market dominance in the long run by the entry of new firms module compatible products (Baldwin and Clark, 1997). An incumbent can also resist to modularity by opposing to the development of a standardized interface (Schilling, 2000). However, the established position of an incumbent could be shaken by an architectural innovation while leaving the modules unchanged (Henderson and Clark, 1990). Modularity has also an impact on the innovative activities of firms. Interfaces and architecture are crucial in modular products. However, according to Fleming and Sorenson (2003) once the interfaces and architecture are set; there is not much possibility for a radical innovation. This environment is favoring incremental innovations. On the other hand, Garud and Kumaraswamy (1995) state that firms can achieve high performance system by reusing some components and substituting others. Authors, argue that the economies of substitution create a technological change process which is neither incremental nor radical but including both of its characteristics.

The above discussions on modularity also encircle the modularity in software. In his seminal article, Parnas (1972) sets the concepts of software modularity and object-oriented programming which contributed to the increase of software productivity. Parnas (1972) claims that modular software brings flexibility and comprehensibility of a system while shortening the software development time. Modularity in software allows breaking down the software project into pieces which would result an easier development. This would also ease to locate, debug and fix any problem. Moreover, modularity improves the reuse of the code in different products as long as the interface matches to the modules. Parnas (1972) divides the advantages of modularity in three distinct aspects. The benefits of modular programming are (1) managerial; multi-site development is made easy with less communication between different developer groups, (2) product flexibility; change in one module does not affect the change of the system and (3) comprehensibility; the system could be studied one module at a time. Similarly, modularity, integrity and upgradability are identified as the three main attributes of a technological system (Garud and Kumaraswamy, 1995).

The modularity theory asserts that many products are inclined towards higher modularity with time. One example given on software modularity had shown that software evolves into a higher degree of modularity with the transition to open source software development practices (MacCormack et al., 2006). However, while the software, as a product, in general evolves into a higher degree of modularity, we do not have much understanding on tracing the module integration in software industry. This work aims to contribute into these issues.

2.2 Diversity

The utility of technological diversity has been discussed by many scholars. There are two competing hypothesis (Breschi et al., 2003). The first one emphasizes that the firms which are focused on R&D activities in a small number of fields are more specialized and this specialization provides a more innovative capability than the diversified firms. The second hypothesis claims that even though some specialization is required, the firms which are more diversified have certain competitive edge through cross-fertilization of different but related technologies. According to Brusoni et al. (2001) who study aircraft engine control systems, it is necessary for multi-technology firms to know more than what they do. A larger knowledge boundary will have positive effects on the coordination of suppliers and the integration of various products for multi-technology firms. Quintana-Garcia and Benavides-Velasco (2008) investigate biotechnology firms. Authors conclude that technological diversity has also a positive effect on the rate of product enhancement and the acceleration of invention which diverges from firms' past activities. Garcia-Vega (2006) demonstrates that among R&D intensive European firms, R&D intensity and the number of patents increase with the degree of technological diversification. Author argues that firms which have diversified technological knowledge can reduce their risks and increase their chances to receive more spillovers. Breschi et al. (2003) claims that firms' technological diversity is linked to the knowledge-relatedness and shows that, firms' innovative activities are expending in a non-random way as a consequence of learning process and of the knowledge features.

2.3 Patent analysis

The importance of the IPR strategies, the rapid rise in the number of patents and the advent of the computerized patent databases drive the development of the patent analysis (Griliches, 1990). The assessment of a legal document such as a patent is a cumbersome process. However, the evaluation of patents is an important step in understanding technological and industrial evolution and/or designing a firm level IPR strategy. Several heuristics and algorithms which are mainly based on citation analysis are developed to answer different questions. Generally these methods are applied to a group of patents which are limited by some International Patent Classification (IPC) codes, firms, a geographical area, inventor(s) or their combinations.

It is accepted that the value of a patent is positively correlated with its features such as the number of forward citations (Trajtenberg, 1990), the patent family size, the number of oppositions and renewals (van Zeebroeck, 2011). The number of claims is also considered as a proxy for the quality of the patent (Lanjouw and Schankerman, 2004).

Patent citation analysis can also give some insight about technology. Dahlin and Behrens (2005), define a heuristic to find radical inventions and by using it they extracted the radical inventions which had shaped the tennis racket industry. Corrocher et al. (2007) confirm that information and communication technologies (ICT) related patents cited from different IPC codes shows a higher rate of innovative activities and the number of IPC classes related to ICT is broader than presumed. Wagner and Cockburn (2010) show that between late 1990s to 2005, Internet firms having unusually highly cited patents are more likely to be acquired. And also firms with patents have a higher chance to survive.

2.3.1 Evolutionary analysis of patents

There are few methods which are developed to analyze patent citation networks with an evolutionary insight. Shibata et al. (2008) cluster citation networks with keywords and detected emerging fields. In this paper we are using the method developed by Hummon and Dereian (1989) which demonstrates a technological trajectory through patent connectivity analysis. This tool is firstly exploited within bibliometrics to study the development of the DNA theory in scientific journals (Hummon and Dereian, 1989). Batagelj (2003) refines the same methodology. He gives an algorithm and applies it to patents and to scientific journals to obtain the main path through which the knowledge flows.Verspagen (2007) uses the same algorithm in a heuristic in order to obtain a network of main paths.

The scientific and technological advances are achieved by the accumulation and recombination of previous knowledge. This is represented by the citation to the prior works in patents and scientific papers. The rationale behind the patent connectivity analysis is to obtain the knowledge flow through citations. It is argued that the patent citation analysis is less prone to error compared to scientific citation. According to (Jaffe and Trajtenberg, 2005) patent citation process is less subjective. Furthermore, it is possible to trace the knowledge flow and the accumulation of knowledge on a specific technology with a citation network analysis. This flow of knowledge reveals the evolution of a technology. The definition of the technological trajectory given by Dosi (1982) forms the background of this perspective. Dosi defines technological paradigm and technological trajectory by referring to Kuhn's definition of scientific paradigms. Dosi claims that scientific and technical advances that are intertwined shape technological change which is limited with the current technological paradigm. This change is also determined by economic, institutional and social factors. According to Dosi (1982); technological paradigm gives "a pattern and a model of solution to a selected set of problems based on selected knowledge derived from natural science with selected materials". As a result, technological paradigm sets the direction of technological trajectories. However, the evolution of technologies shows that while there can be lock-ins, there can also some breakthrough (Arthur, 1989). Discontinuities in the technological trajectory are the results of the emergence of a new technological paradigm (Dosi, 1982).

The heuristic developed by Verspagen (2007) shows technological trajectory of fuel cells. There are other studies which show knowledge flows in various technological fields such as the treatment of coronary artery disease (Mina et al., 2007), data communication standards (Fontana et al., 2009), artificial disc (Barberá-Tomás et al., 2010) and telecom switching industry (Martinelli, 2011). Patent connectivity analysis differs largely from other patent analysis because of its evolutionary perspective.

The popularity of patent citation analysis also brings into attention the processes behind patent citations. It is shown that patent examiners and firm level patenting practices have an influence on citations and this influence could differ according to the technology concerned (Alcácer et al., 2009). It is also noted that patent citation is a noisy proxy for determining knowledge flow (Gomes-Casseres et al., 2006). Moreover, this result is very much related to software patents as well. Controversial issues around software patents such as their quality, rent seeking entities and the problem of litigation are presented in the next section.

2.3.2 Software patents

The appropriability regime model, that Teece (1986) presents, takes into account the nature of the technology concerned and different legal protection schemes. According to the author, trade secrecy is a viable alternative to patents for process inventions. It is claimed that in software industry a combination of trade secrecy and copyright is also an appropriate mechanism to profit (Gambardella and Hall, 2006). It is difficult in the software industry for a follower to imitate an innovator if the algorithm used is not known. In addition, in IPR management point of view, trade secrets and copyrights in the software industry do not generally require very intricate strategies as in the patents.

The nature of software technology is critical in understanding the IPR regime, as well as how patent connectivity analysis should be used to understand technology evolution. The pace of reuse and recombination in software is much faster than the “traditional” sectors. The modularity of software generally results in a product which includes various technologies. Inclusion of a large number of separately patentable elements constitutes a “complex technology” (Cohen et al., 2000). On the other hand, drugs or chemicals are defined as discrete technologies because they are generally comprised of few patentable elements. This definition of technology depending on the number of patents that a commercial product includes imposes industries to opt different IPR management practices. Nelson (1994) argues that a strong IPR regime which yields an increase in patenting could be detrimental for certain technologies. He shows that there are some similarities between radio, aircraft technologies and software which are all “cumulative systems technologies”. Cumulative systems are built on and in combination of previous technologies. In a cumulative systems technology, one or a group of patents on a component can make it difficult or impossible to invent and improve the system. Dosi et al. (2006) claim that a tight IPR regime is more likely to cause rent seeking behaviors such as litigation. Non-producing entities (NPE) are particularly important in software industry to show this rent seeking behaviors.

Non-producing-entities or pejoratively called patent trolls, with their aggressive legal fights, became an important characteristic of the software industry. NPEs can easily take the advantage of an asymmetric risk to enter into a legal battle with a producer because NPEs do not sell any products or services related to their patents. It means that an NPE cannot be sued for an alleged patent infringement in a cumulative systems technology. NPEs can only face to lose in court and incur the legal fees. NPEs can only be plaintiffs. Moreover, established patent strategies (Granstrand, 1999) are not valid against NPEs.

Patent lawyers become important figures due to increasing number of patent litigations. Barthon (2000), in criticizing the strong IPRs, ironically points that the number of patent lawyers is growing faster than the amount of research. According to Allison et al. (2009) 94% of the patent lawsuits are related to software patents. The financial burden caused by NPEs is calculated to be a half a trillion dollars from 1990 through 2010 for the defendent technology firms (Bessen et al., 2011). According to the authors, that loss harms society and there is little evidence of transfer to independent inventors from NPE litigation. By analyzing patent infringement actions taken by universities from 2009 through 2010, Rooksby (2011) argue that there are some remarkable similarities between universities and for-profit actors. However, different patent strategies in a sector could also result with the decrease in the number of patent litigation. Hall and Ziedonis (2007) show that firms in the semiconductor industry changed their IPR strategies into defensive patent portfolio which helped them to curb down the number of litigations between rivals after 1998 to the pre-1982 levels. The increasing number of litigations reveals that, they can also be a proxy for the private value of patents. However, the value of software patents is questioned by Hall and MacGarvie (2010) who could not find a clear answer whether patents awarded to pure software firms increase their market value.

In this section we have overviewed the modularity and technological diversity to examine the behavior of firms in software industry in terms of their software product development strategies. We have also reviewed patent analysis on which we have based our methodology. We discussed the controversial software patent issues because our patent connectivity analysis is done on software related technologies.

In the next section we will present the video indexing technology and its modules, optical character recognition, audio/speech analysis, image analysis that we used for our case study.

3 An overview of video indexing

Video indexing technology is analyzed in this paper. Video indexing enables to "understand" the content of a video file and generates a semantic meaning for specific time frame within the file. The manual construction of an index on digital video database is a time consuming activity which was once carried out by documentalists. However, as the number of video data increased, an automatic, computerized analysis is needed to annotate and classify videos. Snoek and Worring (2005) develop a framework which decomposes video content. In this framework, the author of a video conveys ideas by using visual, auditory and textual channels. Therefore, a video file could be analyzed through visual analysis, auditory analysis and character recognition. In this section, video indexing technology and its three modules; character recognition, audio/speech analysis and image analysis are presented.

The general approach to extract and to index a content of a video file is to use the unimodal approach. In this approach, image analysis, sound and/or speech analysis and/or textual analysis are conducted separately. Most often, the unimodal analysis on video files are carried out only by image analysis. However, the multimodal analysis, which incorporates sound and text, provides more information. In the multimodal, approach various data such as image frames, sound tracks, text obtained from the image frames and spoken words which could be fetched from the audio track are used together (Wang et al., 2000). The advantage of a multimodal analysis is the interaction of modalities which help to have more accurate results. Moreover, apart from experimental softwares, commercial products which use this combined analysis are also reported (Snoek and Worring, 2005).

[Insert Figure 1 here]

An early example of multimodal approach is a system which associates names and faces in news videos without prior face-name association set (Satoh et al., 1999). This system aims to find images of a searched name within a news video database without prior training. The system uses several source of information available in the video. Names are extracted from transcript and video-captions. The transcript of the video is generated by speech recognition analysis. Then, an in-depth semantic analysis is carried out to get names from the transcript text. Face images are also extracted from the video through image analysis. In news videos, names generally appear in video caption. Names appearing in the video captions are obtained through character recognition. All these information obtained from the videos is recorded with their time-code. Then a correspondence is created between information obtained from these various sources. After obtaining as much information as possible from the video content, "co-occurrence" factor is calculated to match names with faces. The transcript, captions and the image quality are better in matching names and faces compared to face recognition carried out on images obtained from surveillance cameras. However, the example given by Satoh et al. (1999) is only one example of matching names and images from news videos. There are many videos which lack easily processed information as given in the example above.

In video indexing there are also other techniques which are used in combination, such as detection of scene change by visual and audio analysis, camera motion, object detection, pattern recognition, character recognition, object tracking, event detection, event recognition etc. The real problem in video indexing is about using all the information obtained through various analysis from a video database, and creating a form such that their combination gives a correct semantic information. Deploying different techniques combinatoraly on large video databases in real time is an important engineering problem.

The result of the extracted information of a video content should be accessible through a multimedia content descriptor. The content descriptor is used to access the user's searched content efficiently. This descriptor contains time-code and tags for particular events within the video. Various standards are designed to contain these information. The MPEG-7 is one of the open and popular standard XML file, which contains the information of a video file separate from the audiovisual content. Then, this XML file is used by a search engine to give a pertinent answer to the searched item(s).

Like many software systems the video indexing is also modular and its modules are separable and interchangeable. This aspect of the video indexing stimulates product differentiation. Through different reconfigurations of modules, it is possible to design products for different markets. For example; the end product could be used by content providers which would help to index their multimedia content. A trimmed version of the video indexing product could also be used in consumer electronics which would help to sort the ever growing private video content.

In the following subsections, the three modules which contribute to video indexing will be presented.

3.1 Character recognition

The first optical character recognition (OCR) related patent is obtained by Tauschek in 1929 in Germany and in 1933, an American inventor filed a similar patent in US (Mori et al., 1992). These inventions were optical and mechanical devices. During the beginning of 1960s several commercial OCRs appeared. In 1962 RCA combined electronics and optical techniques to achieve a very sophisticated OCR. However, it was not incorporated in any product. The first generation of OCRs was able to read only the constrained letter shapes which are symbols specifically designed for machine reading. During this period several firms announced their commercial products in Japan. Starting the end of the 1960s, the second generation of OCR systems was able to recognize hand-printed characters. The first machines which were able to recognize hand-printed characters were marketed by the end of 1960s and early 1970s for automatic postal code sorting. One of the barriers during the 1970s and early 1980s was the recognition of hand written Chinese characters. The characteristics of the third generation of OCR are recognition of poor print-quality characters and large hand-printed character set including Chinese characters. In 1975 an OCR machine was specifically designed to read US Social Security Administration reports printed with more than 256 typewriter fonts with a very different print quality. More information on the historical development of the optical character recognition with an emphasize on Japan is given by Mori et al. (1992).

During the 1980s, several OCR accuracy contests were conducted. Some of the participant software were never commercialized. One of the software's developed between 1985 and 1995 became successful in an OCR accuracy contest was released as an open source software in 2005. This code had never been incorporated in a product when it was closed source[1].

3.2 Audio/speech analysis

Using analog circuitry, Bell Labs in 1952 showed small-vocabulary recognition for spoken digit over phone. Since then important advances have been carried out regularly in automatic speech recognition but there are still technological barriers for an acceptable user experience under some conditions. Until the 1980's it was common to compare the analyzed signal to specific templates and finding the closest match. This comparison process required high computation power. Since then, statistical models such as hidden Markov models replaced the comparison of speech to templates (OShaughnessy, 2008). There are many factors which create technological difficulties in decoding the speech. Technical difficulties for automatic speech recognition are due to the sensitivity of the speech to the background noise, foreign accents, gender, speaking rate etc. In addition, other properties such as emotions of the person can also create different signals for the same speaker (Benzeghiba et al., 2007). Speech signals are considered to have more variability and diversity than image signals. This variance is the biggest challenge for automatic speech recognition (OShaughnessy, 2008).

3.3 Image analysis

Image analysis require many different techniques and approaches to be used together in order to acquire a maximum information from an image. Image segmentation is the process to partition an image into parts which are simpler to analyze. This requires locating objects and boundaries within the image. After the image segmentation, objects should be "recognized" or labeled and classified for the search process.

[1]Presentation of Svetlin Nakov, Tesseract OCR Engine at OpenFest 2009, http://www.slideshare.net/nakov/tesseract-ocr-engine-openfest-2009

[Insert Figure 2 here]

4 Patent analysis and results

In this paper, patent connectivity analysis is utilized to get the name of the firms and patents which had an important contribution to the development of the technology of video indexing and its three modules. The three modules are optical character recognition, audio analysis and image analysis. By using patent connectivity analysis we show the evolution of these four technologies. Patent connectivity analysis shows the technological trajectories and patents which have influenced the development of a technology. This analysis is first developed and used for scientific papers by Hummon and Dereian (1989). The same approach is refined by Batagelj (2003) and improved by Verspagen (2007). This process helps to decrease the number of patents to be analyzed and give an insight to the evolution of the technology.

There are three subsections in this section. The next subsection deals with the data set preparation. Then, patent connectivity analysis methodologies with an emphasis on Search Path Node Pair (SPNP) algorithm are presented. The last subsection shows the results of technological diversity of the firms which have contributed to the development of the technology.

4.1 Data set preparation

The main difficulty in patent analyze is to determine a coherent patent group to be used for the analysis. Generally it is easier to do the patent analysis of a technology which is identified with distinct IPCs. However, software technologies do not have any distinct IPCs. Keyword based search and co-word analysis can be carried out on patent databases in order to overcome the limitations imposed on software technologies. These methods help to refine the patent group and very often they are used in an iterative way.

To find out the necessary keywords which will be used in identifying the initial patent set, video indexing product system architecture (Ozman, 2011) is modeled as in Figure 2. This architecture of the product system, which is set with the help of four experts[2], provides different keywords which are grouped into three main modules of video indexing. We have conducted keyword based search on patent

[2]Consulted experts are two PhD students, their supervisors and an engineer working in this field.

titles and patent abstracts. Further keyword determinations are done iteratively by using n-gram analysis several times on the text generated by patent titles and abstracts. With this procedure we aim to obtain keywords which were possibly ignored during the search processes. Having acquired keywords and patents, we had to discard some of the patents which would heavily change the composition of the patent group. In image analysis with the request of our experts, we had to eliminate patents containing words such as "vehicle" and "car" because the end results were very much related to image processing in the automotive industry. In audio analysis several patents related to video analysis are found in the result set. In order to limit the analysis solely on one technology we also discard patents according to some keywords. In defining patents representing speech and audio analysis we discarded patents having the "video" keyword. In image analysis patents containing keywords such as vehicle, car, video, speech, audio, sound are omitted. However, in defining video indexing we have insisted that all patents should have the keyword "video" in patent title and abstract. All keywords used in defining the four patent groups are given in Table 1

[Insert Table 1 here]

In this research we have used the September 2010 edition of the EPO Worldwide Patent Statistical Database (PATSTAT). The patent group to be analyzed is obtained through keyword search in abstracts and titles of patents granted by USPTO. In order to obtain a more connected patent group and also to catch patents which could not be obtained by keyword search, we have followed the procedures used by van der Heijden (2010). In this procedure, the core group obtained by keyword search is populated with their cited patents. This group constitutes the first generation. The same procedure is carried out on the first generation patents to obtain the second generation of patents. Patents which do not cite directly of indirectly cite the core patents within the first and second generations are eliminated. The end result is two generations of patents which are citing the core patent group. The schematic representation of this procedure which populates the patents obtained by keyword search is shown in Figure 3. The distribution and the number of patents obtained with this procedure for each technology is given in Table 2. The number of shared patents found in two patent groups is given in Table 3. The reason of the same patents found in two different technological groups is due to the citation process which goes to two generations. And also patents from the four patent groups could share in some instances same technology and algorithm such as hidden Markov models which is widely used in speech recognition and image processing.

[Insert Figure 3 here]

[Insert Table 2 here]

[Insert Table 3 here]

The number of patents filed are given in Figure 4.

[Insert Figure 4 here]

4.2 Network calculation

Vertices in the citation network represent patents and edges represent citations between the two patents. The direction of the edge is from cited patents to the citing patents, revealing the direction of the knowledge flows. Vertices in the network could be a start-point, a sink or an intermediate. A start-point is generally an old patent, which is either not citing a patent from the patent group, or not citing any patent at all. A sink is a patent which is not cited by any other patent. An intermediate patent is a patent which is cited by and citing other patents.

In the simple network example given in Figure 5 vertices A and F are start-points, vertices D, H and I are sinks and vertices B, C, E and G are intermediates. The direction of the edges represents the knowledge flows. As an example; the edge B-C displays the knowledge flow from the vertex B to C, which means that the patent C is citing patent B.

A patent citation network has some distinct characteristics. First, there is not any set of edges which connects vertices in such a way that it is possible to reach to the starting vertex. Second, it is directed; all edges in a citation network represent the direction of citation and finally, it is binary because all edges are equal.

Search Path Count (SPC), Search Path Link Count (SPLC) and Search Path Node Pair (SPNP) are the three ways to change a binary citation network into a weighted network. These indicators help to extract the important edges which link as many nodes as possible in the upstream and in the downstream of the knowledge flow. SPC is the simplest indicator which counts the paths between all source and sink vertices. The SPLC traces paths from all vertices to sink vertices and gives the number of times an edge is found in the search path (De Nooy et al., 2005). In this paper we are using the SPNP calculations.

The algorithm of the SPNP calculation is given by Batagelj (2003) and a matrix based formal method is presented by Verspagen (2007). The rest of this section, the explanation of the SPNP calculation is adopted from Fontana et al. (2009). The SPNP calculates the product of the number of upstream and downstream vertices for each edge. In Figure 5 the SPNP value of the edge C-E is $3x4 = 12$. The number of vertices in the upstream, until the startpoint is three (A, B and C), and the number of vertices in the downstream until the sinks is four (E, F, G, and H). The edge which has the highest number of SPNP value shows that it is the edge which links the most upstream vertices to the downstream vertices.

The second step is the identification of the main path. After the calculation of the SPNP value for each edge, the main path starts from the start-point having the highest SPNP value for its edge. In the case that there are some edges with the same SPNP values, then all edges with that value are chosen. Then the same procedure is repeated from the next vertex. This procedure helps to find out the set of linked edges with the highest value from start-point to sink. It represents the knowledge flow of a citation network. Instead of the edges with the highest value, a minimum value could be set and a denser network could be obtained.

[Insert Figure 5 here]

In the example given in Figure 5 the network of main paths start from A and F, and finishes at vertices D, I and H. The knowledge flow follows the edges with the highest values. The knowledge flow starts from the highest valued edge having one of the startpoint which is A in our case and finishes with one of the edge(s) having the highest SPNP value and pointing one of the sink. As the vertices I and H have the equal and the highest value the final knowledge flow map also includes these two vertices. The vertices F (a startpoint) and D (a sink) are dropped because the SPNP value of the edge F-E (F is the startpoint) is lower than the edge A-B and the SPNP value of the edge C-D is lower than the edges G-I or G-H (I and H are other sinks).

Verspagen (2007) have contributed to this methodology by filtering the citation network for different time periods to determine the technological trajectory of fuel cells. In this heuristic, a subnetwork from the main citation network is obtained by extracting patents for a time span starting from the oldest one. Then subsequently the same time span is increased for each new set while the first patent is always the same. To illustrate; we have a set of patents granted starting from 1965 to 2010. Then we analyze numerous patent sets which are granted between 1965 to 1970, 1965 to 1975, 1965 to 1980, and so forth. For each subset we conduct the SPNP calculations, then by adding up all main paths we obtain a temporal network of main paths. This new network which is less dense then the whole network shows the evolution of the main paths. If the subnetworks are obtained with a smaller time span then there is a high probability of a temporal network of main paths with a higher number of vertices.

In the next subsections, the network of main paths, results obtained from the four patent sets are given. In all figures and tables, year represents the patent filing year.

4.2.1 Character recognition

The network of main paths of character recognition is represented in Figure 6. The development trajectory of the textual modality starts to diverge into two different technical fields after 1983. From that patent there are two branches, one is extending to up, denoted as U, and the other one to the down (D axis) on Figure 6. The one which is extending to the upper axis is the development of the text extraction and recognition from a captured image. This extraction is applied in different circumstances such as from automobile number plates and id cards. Starting from the patent awarded to IBM in 1991 in U axis, two clusters emerge. These two clusters of patents are both related to hand writing recognition inventions. On the other hand, the axis stretching to down, the D axis, patents are related to the optimization, enhancement of the optical character reader software. In Table 4 the highest cited patents related to character recognition is given.

[Insert Figure 6 here]

4.2.2 Audio and speech analysis

Figure 7 shows the evolution of main paths of audio and speech analysis. From a patent filed in 1988 and issued in 1991 the development of the audio/speech main paths follows two different axis, one is lying toward up and the other one toward down. This patent is about a method of speech recognition and user led training which is within the supervised learning realm. In this example the supervised learning is a function which "learns" to classify speech with the help of a human interaction. From this patent the branch extending to the up, the U axis, is about speech recognition devices which are working in client-server mode. In this mode the client (PC, handheld devices etc.) with a limited capability send voices to a server which analyzes and send back a response. Patents on the U axis are focused on voice recognition in servers and interactive services. The other branch which is extending to down, D axis, is mainly dealing with methods on training of speech recognition systems used for speaker identification, voice activated devices and speech-based authentication. The highest cited patents within the audio and speech analysis related patents are given in Table 6.

[Insert Figure 7 here]

4.2.3 Image analysis

The network of main paths of the image analysis is given in Figure 7. The axis towards up, U axis, contains patents which are related to pattern recognition systems in image but also to speech. The patent on the trifurcation is the first in the series of image recognition systems using neural network systems found on the axis U1. However, on the same axis, patents filed after 1998 and issued after 2000 are less generic and more concentrated on face recognition systems. Last patents filed after 2003 and issued in 2009 are all related to classification systems for consumer digital images and face detection and recognition. U2 axis is about pattern classification which extends until 1996 and D axis extends until 1986. In Table 8 the highest cited patents related to image analysis is given.

[Insert Figure 8 here]

4.2.4 Video Indexing

Patents obtained from the network of main paths of video indexing are all related to information retrieval from a video file. The first patents on the main path of video indexing are about television systems. Some topics in this patent batch are related to generating formatted information on videos for electronic publishing, individual recognition on videos, object recognition, facial sensing and extraction of facial biometric data from image. The last patent is about scene analysis and detecting moving objects which are occluded in the background image. However, two patents are related to detection of moving objects from a video stream which would be presumed to be used in driverless cars due to the assignee name. Table 10 gives patents with the highest number of citation within the video indexing patents.

[Insert Figure 9 here]

4.2.5 General evaluation of the network calculations

Patents on the network of main paths (Figures 6, 7, 8 and reffig:spnp$_v ideo_i ndexing)andpatentswithth$
$producingentities.$

We have obtained several branches in the network of main paths on the development of the three building blocks of the video indexing (Figures 6, 7, 8). These results help to distinguish and categorize distinct sub-branches of the software technology. Figure 10 shows that the cumulative number of patents on the network of main paths for the three modules is higher than the video indexing one. This is due to the set of patents which are related to each other and the novelty of the video indexing technology which give lower patenting rate as shown in Figure 4.

The network of main paths of video indexing and its three modules are not sufficient to depict the intrafirm and interfirm effects of modularity (Garud and Kumaraswamy, 1995; Langlois and Robertson, 1992; Sanchez and Mahoney, 1996). Lack of information on which products embody which patents is a problem. From the networks of main paths we obtained important inventions which have contributed to the development of video indexing and its three modules. Baldwin and Clark (1997) showed that there are two groups in modular production, the one which sets the architecture and the second one which produces the required modules according to the architecture. According to Baldwin and Clark (1997) the module producer should fill a technological gap and then either move to another technological area or increase the module's performance. During the early stage of development a decentralized production system allows new entrants. Yet, during the systemic innovation phase vertical integration have the advantage to coordinate the production of modules for less cost (Langlois and Robertson, 1992).

By analyzing the four patent groups, we can argue that some multi-technology firms could conduct a vertical integration within their firm. Even though there are firms having patents on numerous networks of main paths, there is one firm (Siemens) which has patents on all of the four networks of main paths. It is possible that this firm has a vertical integration in video indexing and it is also found that Siemens is active in large scale surveillance technologies. However, few patents are same in the image analysis technology and video indexing network of main paths. This could be due to shared patents among different patent groups of similar technologies, algorithms based on such as hidden Markov model. However, we consider that these patents are relevant and important in the development of their respective patent groups.

There are some common patents between video indexing and the three other patents. It has been found that Siemens is a firm which has patents on all of the four networks of main paths given in Figures 6, 7, 8, 9 and Tables 5, 7, 9, 11. Two of their patents appear in the network of main paths of image analysis and video indexing. We have found seven patents from 1996 to 2004 which are common between image analysis and video indexing. There are three firms which have patents both in video indexing and character recognition network of main paths.

The patent connectivity analysis cannot catch the modules which have adopted the free, libre and open source software (FLOSS) development model. However, whether the adoption of FLOSS in video indexing brings a higher degree of modularity, as shown by MacCormack et al. (2006), has to be investigated. However such development would force video index software producers to adopt a modular IPR strategy (Henkel and Baldwin, 2009).

Due to the patent analysis in software technologies which do not have specific IPC we have faced few difficulties. In order to analyze any technology which does not have a specific IPC(s) we are constrained with keyword based search. However, the quality of the database, patent fields that it presents in the database play an important role in the quality of the results. Unfortunately, PATSTAT has only the title and abstract of the patents and do not contain the patent claims in which there is more precise information about the content of the patent. On the other hand a patent database which allow full text search might also contribute to obtain false positives. A fine tuned text mining tool might give a better result.

4.3 Technological diversity index

In order to understand the technological diversity of firms and also of the patents, technology classification table (Schmoch, 2008) is used with the Herfindahl index. Technology classification is based on IPC8 codes and classifies IPC codes into 35 different technological fields. This table is also known as the WIPO IPC-Technology Concordance Table[3]. We calculate various diversity indexes. The first calculation is done for firms having a patent on the network of main paths found in the previous section. The second one is the diversity index calculation for each of the four patent groups. The last one is the calculation of the diversity index mean for each firm

[3] `http://www.wipo.int/ipstats/en/statistics/patents`

having at least a patent within one of the module. To calculate the value of any diversity index for a specific year, we take into account patents which are filed for the previous five years. The diversity index of a firm is calculated as follow.

$$H = \sum_{i=1}^{35} (\frac{n}{N})^2 \tag{1}$$

i represents one of the 35 technological fields given by the WIPO IPC-Technology Concordance Table. n is the total number of patent within a particular technological field and N is the total number of patents. The value of H (Herfindahl index) ranges between 0 and 1. The diversity index is $1 - H$, the greater the value the greater the diversity.

Follow-up is an example of the calculation of the diversity index of a firm which have a patent on the network of main paths. A patent filed in year 2004 and awarded to Honda Motors Co. appears on the network of main paths of the video indexing. The technological diversity of Honda Motors Co. is calculated by taking into account all patents that are filed by the same company between the start of the year 2000 and the end of 2004. N is the total number of the patents obtained by the Honda Motors Co. between 2000 and 2004. n is the number of patents which is found to be within one of the 35 technological field given in the IPC-Concordance table. We use equation 1 to obtain the diversity index of the Honda Motor Co. for the year 2004.

The second diversity index calculation is done for each of the four patent groups. For a diversity index of a specific year of one of the patent groups, we use the equation 1 by adding up patents between the specific year and the previous four years.

The arithmetical mean of firms' diversity indexing of one of the patent groups for each year is calculated by finding first firms which have at least one patent for a specific year. Then we calculate each firms diversity index as in the second calculation and in the final step we add up all diversity indexes and divide it by the number of firms.

Diversity index for the four patent groups are given in Figures 11, 12, 13, 14. In each of these four graphs, the technological diversity of firms having a patent on the network of main paths is labeled as "Firm on SPNP", the general diversity of the technology is labeled as one of the technological name such as "video indexing, textual, auditory or visual" and the arithmetical mean of technological diversity of firms is labeled as "Diversity Mean". All of these indicators are given within the same graph. The idea in each of these graphs is to position diversity index of firms which have an impact on the development of the technology vis-a-vis technological diversity and arithmetical mean of firms' diversity.

[Insert Figure 11, 12, 13, 14 here]

It is found that the group of patents made of textual, audio and visual technologies, which are the main modules of the video indexing, have a stable diversity. However, there is a stable decrease of the diversity within the video indexing patents after 1990.

In rapidly changing technological environments firms focus on their core technologies while depending on others for complementary ones (Garud and Kumaraswamy, 1995). Firms' diversity in Figures 11, 12, 13, 14, show that there are different firms contributing to the development of the technology. It could be asserted that firms having a very low diversity focus solely on a distinct technology. These firms could provide the complementary technologies, modules which would be deployed by the system integrator firms in video indexing. On the other hand, firms having high diversity show that they have larger firm boundaries (Brusoni et al., 2001).

There are three groups of firms which have a contribution to the development of the technology. The first one is the diverse one, with a diversity index higher than the group of patents for that technology. The second one has more or less the same diversity as the patents of the technology. The last group are firms which are not at all diverse, ie. firms which have patents having a very small number of IPCs or within only one IPC. Figures 11, 12, 13 show that the diversity of firms which have contributed to the development of the three modules are multi-technology firms with a high diversity index. However, in video indexing, Figure 14, firms, which have an impact on the development of the technology, have diversity indexes scattered around the diversity values of patents of the video indexing and the mean diversity of firms. The reason is that firms contributing to the development of the video indexing are less diverse and more concentrated on their core competencies.

System integrators in video indexing could determine, through citation network analysis, firms and technologies which had an impact on the technological development and obtain required off-the-shelf components from these firms (Fleming and Sorenson, 2003). Moreover, a modularly upgradable video indexing system would help to reduce cost of development and decrease the development time (Garud and

Kumaraswamy, 1995). However, the number of patents, yearly distribution of the patents and the results of the diversity indexes of the four technologies show that video indexing is a newer technology. These results reveal that the modules are more mature than video indexing.

5 Conclusion

The patent analysis presented in this paper contains two main novel approaches which could be used to understand the technological development of a modular software technology. First, we have used the product architecture of a software technology, in our case video indexing, to determine keywords to be used in patent search. Second, from this product system architecture, we have identified three other distinct technologies which are in a more advanced development phase compared to video indexing. These technologies are character recognition, audio/speech analysis and image analysis. The analysis of these technologies helps to define the firms which are active in these four fields. Nevertheless, keyword based search on titles and abstracts have some shortcomings compared to IPC code based analysis. Keyword based search could be refined using more keywords and it could also be executed on patent claims for a more pertinent analysis. With the approach presented in this paper, we have observed four basic results. First, we have identified a vertically integrated firm. Second, we have spotted different development trajectories of software related technologies. Third, we have found that in each analyzed patent groups, the most cited patents do not have a technological impact. Fourth, we have identified that the firms having an impact on the development of the technology either have high diversity leading to a multi-technology firm or have a very small diversity which points to a very specialized firm.

Acknowledgment: I am grateful to Müge Özman for her helpful and critical comments of this work. I also thank to Mathieu Beauvais, Titus Zaharia, Andrei Bursuc, Raluca-Diana Petre for their help to set the architecture of the product system and their comments on video indexing. This work is funded by Alcatel-Lucent Bell Labs, MODEUS research project.

References

Alcácer, J., Gittelman, M., and Sampat, B. (2009). Applicant and examiner citations in U.S. patents: An overview and analysis. *Research Policy*, 38(2):415–427.

Allison, J. R., Lemley, M. A., and Walker, J. (2009). Extreme Value or Trolls on Top? The Characteristics of the Most-Litigated Patents. *University of Pennsylvania Law Review*, 158(1).

Arthur, W. (1989). Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal*, 99(394):116–131.

Baldwin, C. Y. and Clark, K. (1997). Managing in an age of modularity. *Harvard Business Review*, 75(5):84–93.

Barberá-Tomás, D., Jiménez-Sáez, F., and Castelló-Molina, I. (2010). Mapping the importance of the real world: The validity of connectivity analysis of patent citations networks. *Research Policy*, 40:473–486.

Barthon, J. H. (2000). Reforming the Patent System. *Science*, 287(5460):1933–1934.

Batagelj, V. (2003). Efficient algorithms for citation network analysis. *arXiv*, cs/0309023:1–27.

Benzeghiba, M., Demori, R., Deroo, O., Dupont, S., Erbes, T., Jouvet, D., Fissore, L., Laface, P., Mertins, a., and Ris, C. (2007). Automatic speech recognition and speech variability: A review. *Speech Communication*, 49(10-11):763–786.

Bessen, J., Ford, J., and Meurer, M. (2011). The Private and Social Costs of Patent Trolls. *Boston University School of Law Working Paper*, 11(45).

Breschi, S., Lissoni, F., and Malerba, F. (2003). Knowledge-relatedness in firm technological diversification. *Research Policy*, 32(1):69–87.

Brusoni, S., Prencipe, A., and Pavitt, K. (2001). Knowledge specialization, organizational coupling, and the boundaries of the firm: Why do firms know more than they make? *Administrative Science Quarterly*, 46(4):597–621.

Cohen, W. M., Nelson, R. R., and Walsh, J. P. (2000). Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not). *NBER Working Paper Series*, (7552).

Corrocher, N., Malerba, F., and Montobbio, F. (2007). Schumpeterian patterns of innovative activity in the ICT field. *Research Policy*, 36(3):418–432.

Dahlin, K. B. and Behrens, D. M. (2005). When is an invention really radical? Defining and measuring technological radicalness. *Research Policy*, 34(5):717–737.

De Nooy, W., Mrvar, A., and Batagelj, V. (2005). *Exploratory network analysis with Pajek*. Cambridge University Press, Cambridge.

Dosi, G. (1982). Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11(3):147–162.

Dosi, G., Marengo, L., and Pasquali, C. (2006). How much should society fuel the greed of innovators? On the relations between appropriability, opportunities and rates of innovation. *Research Policy*, 35(8):1110–1121.

Fleming, L. and Sorenson, O. (2003). Navigating the technology landscape of innovation. *MIT Sloan Management Review*, pages 15–24.

Fontana, R., Nuvolari, A., and Verspagen, B. (2009). Mapping technological trajectories as patent citation networks. An application to data communication standards. *Economics of Innovation and New Technology*, 18(4):311–336.

Gambardella, A. and Hall, B. H. (2006). Proprietary versus public domain licensing of software and research products. *Research Policy*, 35(6):875–892.

Garcia-Vega, M. (2006). Does technological diversification promote innovation? *Research Policy*, 35(2):230–246.

Garud, R. and Kumaraswamy, A. (1995). Technological and organizational designs for realizing economies of substitution. *Strategic Management Journal*, 16:93–109.

Gomes-Casseres, B., Hagedoorn, J., and Jaffe, A. B. (2006). Do alliances promote knowledge flows? *Journal of Financial Economics*, 80(1):5–33.

Granstrand, O. (1999). *The Economics and Management of Intellectual Property*. Edward Elgar, Chaltenham, UK.

Griliches, Z. (1990). Patent statistics as economic indicators: a survey. *Journal of Economic Literature*, 28(4):1661–1707.

Hall, B. H. and MacGarvie, M. (2010). The private value of software patents. *Research Policy*, 39(7):994–1009.

Hall, B. H. and Ziedonis, R. H. (2007). An empirical analysis of patent litigation in the semiconductor industry. *University of California at Berkeley working paper*, (January):4–7.

Henderson, R. M. and Clark, K. B. (1990). Architecturai Innovation : The Reconfiguration of Existing Product Technologies and the Failure of Established Firms. *Administrative Science Quarterly*, 35:9–30.

Henkel, J. and Baldwin, C. Y. (2009). Modularity for Value Appropriation : Drawing the Boundaries of Intellectual Property.

Hummon, N. and Dereian, P. (1989). Connectivity in a citation network: The development of DNA theory. *Social Networks*, 11(1):39–63.

Jaffe, A. B. and Trajtenberg, M. (2005). *Patents, Citations, and Innovations*. The MIT Press.

Langlois, R. N. and Robertson (1992). Networks and innovation in a modular system: Lessons from the microcomputer and stereo component industries. *Research Policy*, 21(4):297–313.

Lanjouw, J. O. and Schankerman, M. (2004). Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators. *The Economic Journal*, 114(495):441–465.

MacCormack, A., Rusnak, J., and Baldwin, C. Y. (2006). Exploring the Structure of Complex Software Designs: An Empirical Study of Open Source and Proprietary Code. *Management Science*, 52(7):1015–1030.

Martinelli, A. (2011). An emerging paradigm or just another trajectory? Understanding the nature of technological changes using engineering heuristics in the telecommunications switching industry. *Research Policy*, 41(2):414–429.

Mina, A., Ramlogan, R., Tampubolon, G., and Metcalfe, J. (2007). Mapping evolutionary trajectories: Applications to the growth and transformation of medical knowledge. *Research Policy*, 36(5):789–806.

Mori, S., Suen, C. Y., and Yamamoto, K. (1992). Historical review of OCR research and development. *Proceedings of the IEEE*, 80(7).

Nelson, R. R. (1994). Intellectual property protection for cumulative systems technology. *Columbia Law Review*, 94(8):2674.

Ozman, M. (2011). Management & Innovation Modularity , Industry Life Cycle and Open Innovation. *Journal of Technology Management & Innovation*, 6(1):26–37.

OShaughnessy, D. (2008). Invited paper: Automatic speech recognition: History, methods and challenges. *Pattern Recognition*, 41(10):2965–2979.

Parnas, D. (1972). On the criteria to be used in decomposing systems into modules. *Communications of the ACM*.

Quintana-Garcia, C. and Benavides-Velasco, C. A. (2008). Innovative competence, exploration and exploitation: The influence of technological diversification. *Research Policy*, 37(3):492–507.

Rooksby, J. H. (2011). University initiation of patent infringement litigation. *John Marshall Review of Intellectual Property Law*, 10:623–694.

Sanchez, R. and Mahoney, J. T. (1996). Modularity, flexibility and knowledge management in product and organization design. *Strategic Management Journal*, 17(Winter Special Issue):63–76.

Satoh, S., Nakamura, Y., and Kanade, T. (1999). Name-it: Naming and detecting faces in news videos. *Multimedia, IEEE*, 6(1):22–35.

Schilling, M. A. (2000). Toward a General Modular Systems Theory and Its Application to Interfirm Product Modularity. *The Academy of Management Review*, 25(2):312.

Schmoch, U. (2008). Concept of a Technology Classification for Country Comparisons, Final Report to the World Intellectual Property Organisation (WIPO). Technical Report June, Fraunhofer Institute for Systems and Innovation Research, Karlsruhe, Germany.

Shibata, N., Kajikawa, Y., Takeda, Y., and Matsushima, K. (2008). Detecting emerging research fronts based on topological measures in citation networks of scientific publications. *Technovation*, 28(11):758–775.

Simon, H. A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society*, 106(6):467–482.

Snoek, C. and Worring, M. (2005). Multimodal video indexing: A review of the state-of-the-art. *Multimedia Tools and Applications*, 25(1):5–35.

Teece, D. J. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, 15(6):285–305.

Trajtenberg, M. (1990). A Penny for Your Quotes: Patent Citations and the Value of Innovations. *The RAND Journal of Economics*, 21(1):172–187.

van der Heijden, S. (2010). Landscaping of an Emerging Technology by Bibliometric Analyses; A Case Study on Wireless Energy Transfer. *Master Thesis, Eindhoven University of Technology.*

van Zeebroeck, N. (2011). The puzzle of patent value indicators. *Economics of Innovation and New Technology*, 20(1):33–62.

Verspagen, B. (2007). Mapping technological trajectories as patent citation networks: A study on the history of fuel cell research. *Advances in Complex Systems*, 10(1):93–115.

Wagner, S. and Cockburn, I. M. (2010). Patents and the survival of Internet-related IPOs. *Research Policy*, 39(2):214–228.

Wang, Y., Liu, Z., and Huang, J. (2000). Multimedia content analysis-using both audio and visual clues. *IEEE Signal Processing Magazine*, 17(6):12–36.

Appendix

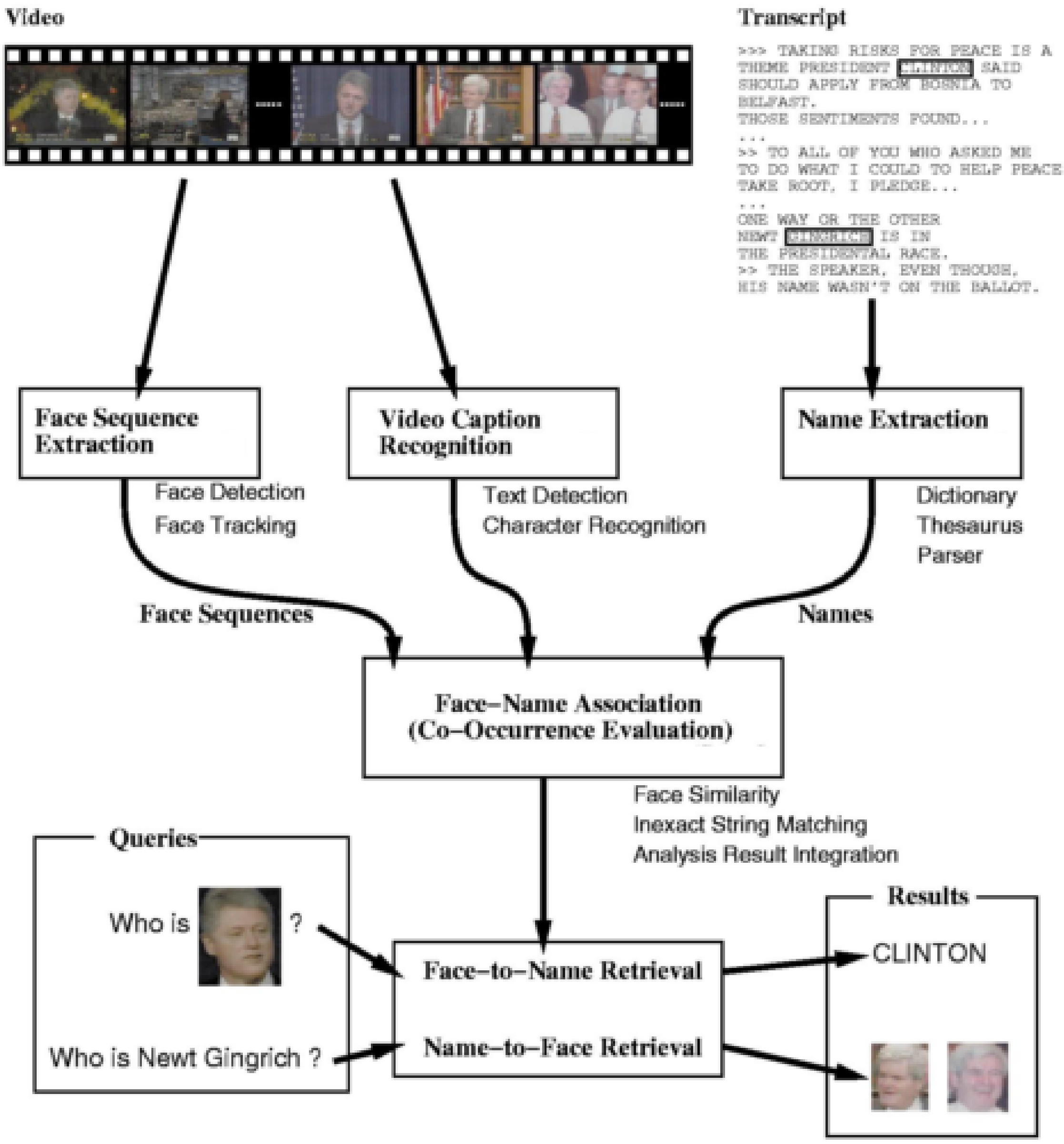

Figure 1: An example of multi-modal video indexing (Satoh et al., 1999).

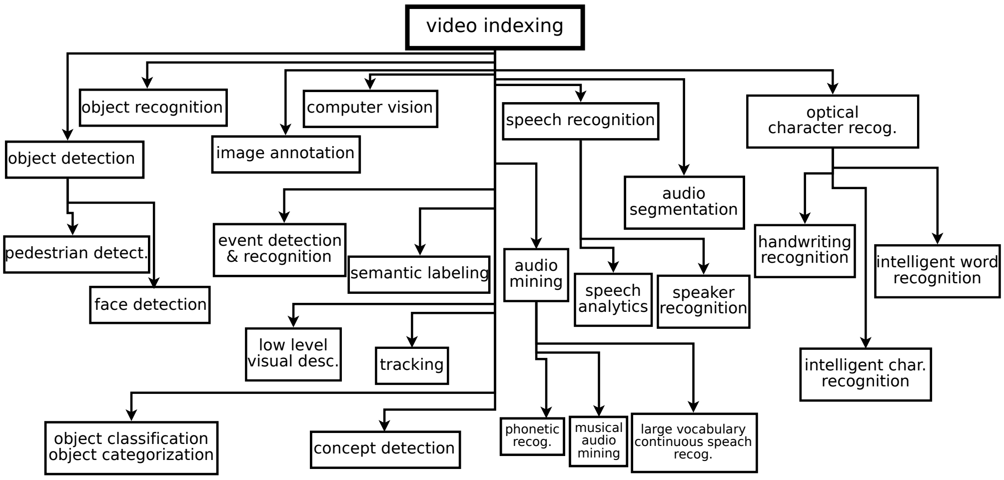

Figure 2: Product architecture of the video indexing.

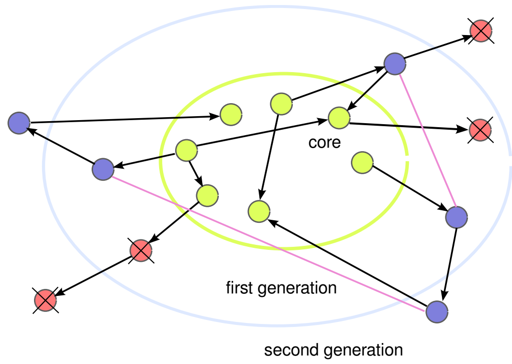

Figure 3: Populating the number of patents through citations (van der Heijden, 2010).

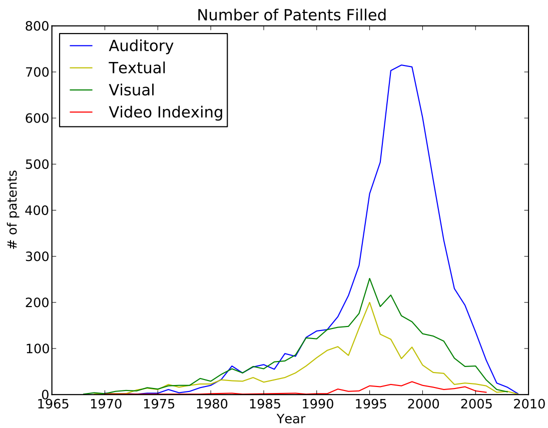

Figure 4: Yearly distribution of the number of filed patents.

Table 1: Keywords used for each patent groups.

image analysis	**speech/audio analysis**	**character recognition**	**video indexing**
object detection	speech recognition	ocr	video*classif
object recognition	speech recognizer	optical character recognition	video index
facial detection	voice recognition	paper to computer	video retriev
facial recognition	audio segmentation	paper-to-computer	object detection
face detection	audio mining	handwriting recognition	object recognition
face recognition	speech analytics	intelligent character recognition	facial detection
pedestrian detection	speaker recognition	intelligent word recognition	facial recognition
people detection	phonetic recognition		face detection
computer vision	speech to text		face recognition
image annotation	speech-to-text		pedestrian detection
event detection	sound pattern		people detection
event recognition	silence detection		computer vision
semantic labeling	speaker identification		image annotation
concept detection			event detection
pattern recognition			semantic labeling
visual descriptor			concept detection
object classification			visual descriptor
object categorization			object classification
visual descriptor			object categorization
			visual descriptor
			event recognition
- vehicle	- video		+ video
- car			
- video			
- speech			
- audio			
- sound			

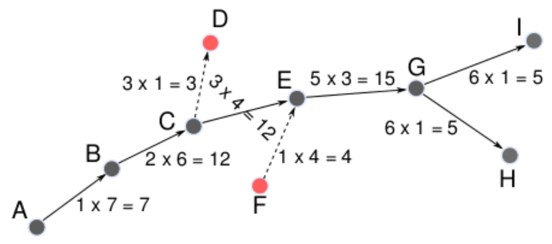

Figure 5: SPNP value of each edge of a representative network.

Table 2: Number of patents in each group.

	core	sum of all generations	number of citation	av. degree
image analysis	893	3,144	12,725	8.1
speech/audio analysis	2,777	6,781	45,602	13.4
character recognition	481	1,880	5,494	5.8
video indexing	113	240	513	4.3

Table 3: Number of common patents.

	image	speech/audio	character recog.	video indexing
image analysis	x	479	320	131
speech/audio analysis		x	129	20
character recog.			x	2
video indexing				x

Table 4: Top 20 cited patents related to character recognition patent group and their assignees.

# of citations	patent num	Pub. year	Assignees name
595	5692073	1997	Xerox
586	4916441	1990	CliniCom Inc.
580	5051736	1991	IBM
489	5677955	1997	Bell Communications Research,Financial Services Technology Consortium,The First National Bank of Boston
390	4387297	1983	Symbol Technologies
312	4409470	1983	Symbol Technologies
309	5721788	1998	Corbis
299	5410141	1995	Norand
297	5978773	1999	NeoMedia Technologies
281	5378883	1995	Omniplanar Inc.
276	6964374	2005	Lucent Technologies Inc.
268	5354977	1994	Roustaei; Alex
257	5804803	1998	IBM
235	6400996	2002	Hoffberg, Hoffberg-Borghesani
234	5756981	1998	Symbol Technologies
230	4264808	1981	NCR
216	5532467	1996	Roustaei; Alex
211	5337361	1994	Symbol Technologies
210	4972496	1990	Grid Systems
206	6311214	2001	Digimarc

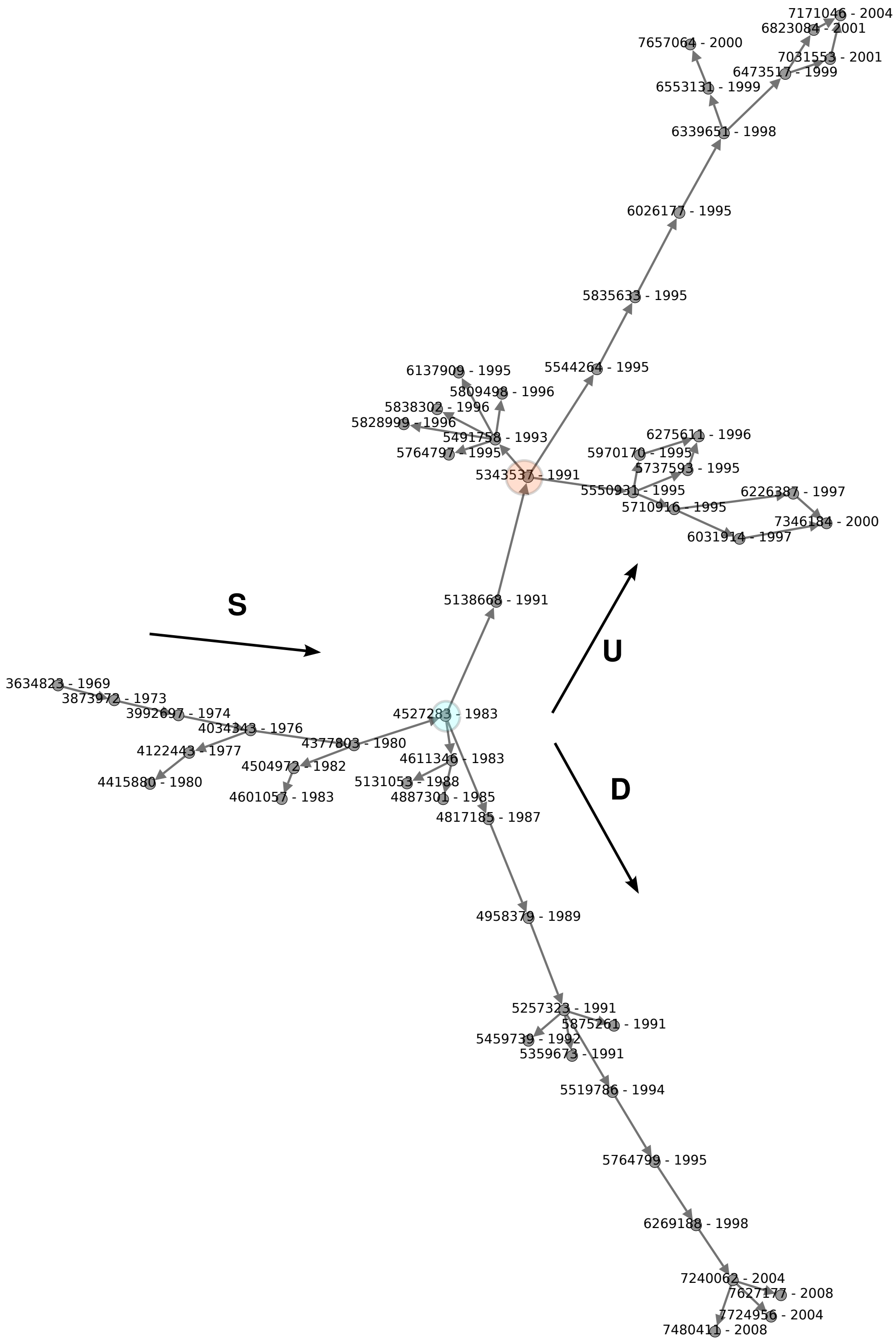

Figure 6: Network of main paths of the character recognition determined with SPNP. Nodes are labeled with publication number - application filing year.

Table 5: Firms on the network of main paths of character recognition. The location column shows the placement of patents within the related figure. U points out the axis stretching to up and S to down.

Patent num	Assignees name	Pub. year	location
7480411	IBM	2008	D
7627177	IBM	2008	D
7171046	SRI International	2004	U
7240062	iArchives	2004	D
7724956	Gannon Technologies Group LLC	2004	D
6823084	SRI International	2001	U
7031553	SRI International	2001	U
7346184	Digimarc	2000	U (cluster)
7657064	Digimarc	2000	U
6473517	Siemens	1999	U
6553131	Siemens	1999	U
6269188	Canon	1998	D
6339651	Kent Ridge Digital Labs	1998	U
6031914	University of Minnesota	1997	U (cluster R)
6226387	University of Minnesota	1997	U (cluster R)
5809498	Panasonic	1996	U (cluster L)
5828999	Apple	1996	U (cluster L)
5838302	Casio	1996	U (cluster L)
6275611	Motorola	1996	U (cluster R)
5544264	IBM	1995	U
5550931	IBM	1995	U (cluster R)
5710916	Panasonic	1995	U (cluster R)
5737593	IBM	1995	U (cluster R)
5764797	Microsoft	1995	U
5764799	Research Foundation of State of State of New York	1995	D
5835633	IBM	1995	U
5970170	Kodak	1995	U (cluster)
6026177	The Hong Kong University of Science & Technology	1995	U
6137909	The USA Navy	1995	U (cluster L)
5519786	TRW Inc.	1994	D
5491758	IBM	1993	U (cluster L)
5459739	OCLC Online Computer Library Center	1992	D
5138668	Sony	1991	U
5257323	Canon	1991	D
5343537	IBM	1991	U
5359673	Xerox	1991	D
5875261	IBM	1991	D
4958379	Sumitomo	1989	D
5131053	Caere	1988	
4817185	Sumitomo	1987	
4887301	Dest	1985	
4527283	Tokyo Keiki	1983	bifurcation
4601057	Omron Tateisi Electronics	1983	S
4611346	IBM	1983	S
4504972	Siemens	1982	S
4377803	IBM	1980	S
4415880	Texas Instruments	1980	S
4122443	Scan Optics	1977	S
4034343	Xerox	1976	S
3992697	Scan-Data	1974	S
3634823	International Standard Electric	1969	S

Table 6: Top 20 cited patents related to audio and speech analysis patent group and their assignees.

# of citations	patent num	Pub. year	Assignees name
797	5892900	1999	InterTrust Technologies
591	5247347	1993	Bell Atlantic Network Services
504	5086385	1992	Custom Command Systems
503	5675507	1997	Bobo, II; Charles R.
472	5732074	1998	CellPort Labs
461	5353331	1994	Bell Atlantic Network Services
460	5335276	1994	Texas Instruments
446	4757267	1988	Applied Telematics
424	5327486	1994	Bell Communications Research
405	4949187	1990	Cohen; Jason M.
404	5721827	1998	Logan; James
392	5915001	1999	Vois
382	4305131	1981	Best; Robert M.
365	5652789	1997	Wildfire Communications
356	5884262	1999	Bell Atlantic Network Services
356	5410343	1995	Bell Atlantic Network Services
350	5297031	1994	Chicago Board of Trade
337	5334974	1994	Moore, Jr.; Daniel D.,Simms; Charles G.,Simms; James R.
332	5497373	1996	Ericsson Messaging Systems Inc.
322	5132992	1992	Browne; H. Lee,Yurt; Paul

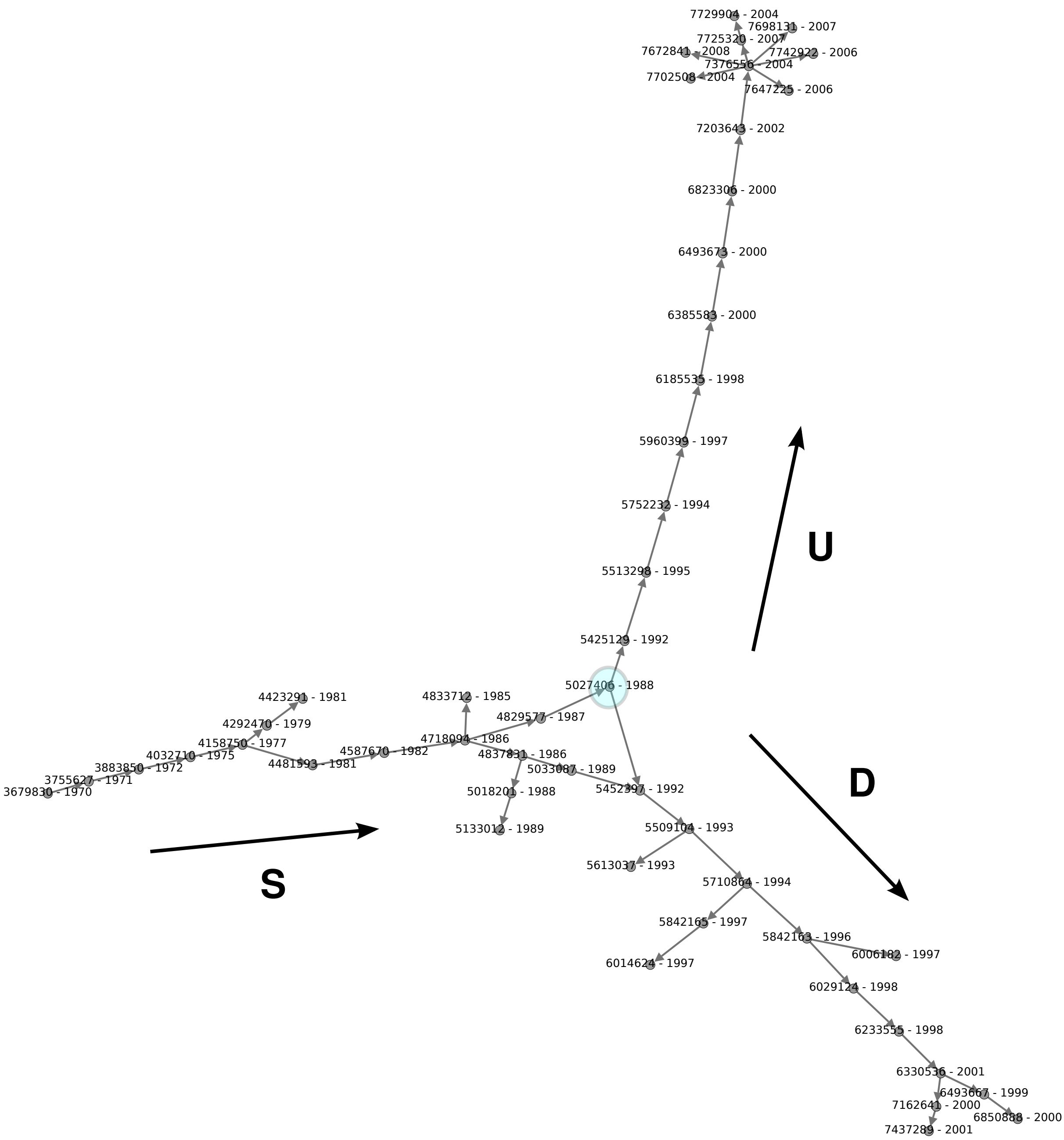

Figure 7: Network of main paths of the speech/audio analysis determined with SPNP. Nodes are labeled with publication number - application filing year.

Table 7: Firms on the network of main paths of auditory. The location column shows the placement of patents within the related figure. U points out the up and D to down.

Patent num	Assignees name	Pub. year	location
7672841	Phoenix Solutions	2008	U
7698131	Phoenix Solutions	2007	U
7725320	Phoenix Solutions	2007	U
7647225	Phoenix Solutions	2006	U
7376556	Phoenix Solutions	2004	U
7702508	Phoenix Solutions	2004	U
7729904	Phoenix Solutions	2004	U
7203643	Qualcomm	2002	U
6330536	AT& T .	2001	D
7437289	IBM	2001	D
6385583	Motorola	2000	U
6493673	Motorola	2000	U
6823306	Telesector Resources Group	2000	U
6850888	IBM	2000	D
7162641	IBM	2000	D
6493667	IBM	1999	D
6029124	Dragon Systems	1998	D
6185535	Ericsson	1998	U
6233555	AT& T	1998	D
5842165	Nynex Science & Technology	1997	D
5960399	GTE Internetworking	1997	U
6006182	Northern Telecom	1997	D
6014624	NYNEX Science and Technology	1997	D
5842163	SRI International	1996	D
5513298	IBM	1995	U
5710864	Lucent Technologies	1994	D
5752232	Lucent Technologies	1994	U
5509104	AT& T Corp.	1993	D
5613037	Lucent Technologies	1993	D
5425129	IBM	1992	U
5452397	Texas Instruments	1992	D
5033087	IBM	1989	S
5133012	Toshiba	1989	S
5018201	IBM	1988	S
5027406	Dragon Systems	1988	S
4829577	IBM	1987	S
4718094	IBM	1986	S
4837831	Dragon Systems	1986	S
4833712	IBM	1985	S
4587670	AT& T Bell Laboratories	1982	S
4423291	Siemens	1981	S
4481593	Exxon	1981	S
4292470	Interstate Electronics	1979	S
4158750	Nippon Electric	1977	S
4032710	Threshold Technology	1975	S
3883850	Threshold Technology	1972	S
3755627	US Navy	1971	S

Table 8: Top 20 cited patents related to image analysis patent group and their assignees.

# of citations	patent num	Pub. year	Assignees name
620	4870302	1989	Xilinx
333	5613012	1997	Smarttouch
289	6161130	2000	Microsoft
288	5963134	1999	Checkpoint Systems
280	5410344	1995	Arrowsmith Technologies
272	5765176	1998	Xerox
265	5862260	1999	Digimarc
261	4582985	1986	Lofberg, Bo
248	6236365	2001	TracBeam
242	6122403	2000	Digimarc
239	5446891	1995	IBM
235	6400996	2002	Hoffberg ,Hoffberg-Borghesani
226	5440723	1995	IBM
226	5185667	1993	TeleRobotics International
225	5892903	1999	Internet Security Systems
219	4965725	1990	Nueromedical Systems
219	5313953	1994	InControl
206	5893095	1999	Virage
206	4553261	1985	Froessl, Horst
204	6405132	2002	Intelligent Technologies International

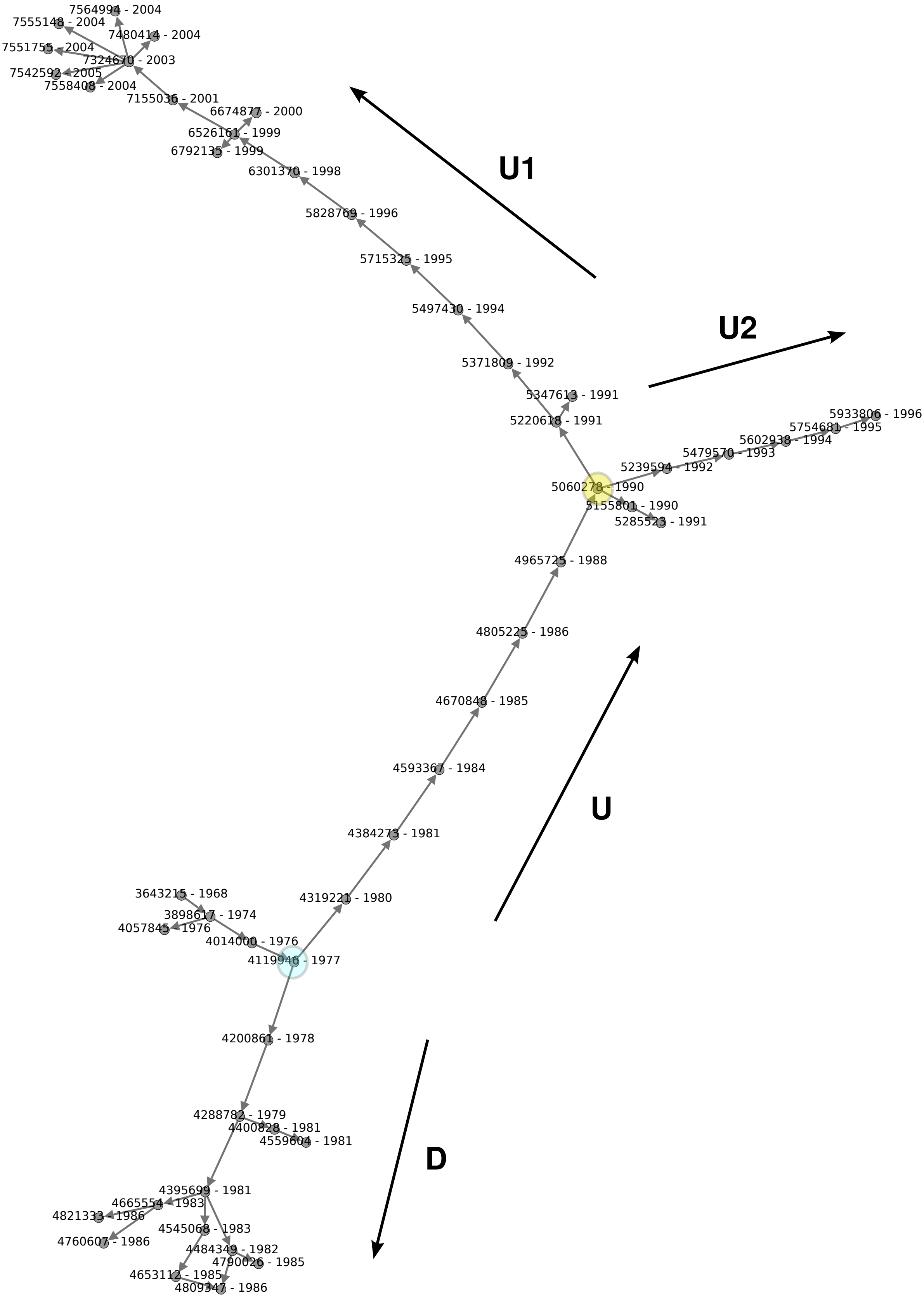

Figure 8: Network of main paths of the image analysis determined with SPNP. Nodes are labeled with publication number - application filing year.

Table 9: Firms on the network of main paths of the image analysis.

Patent num	Assignees name	Pub. year	location
7542592	Siemens	2005	U1
7480414	IBM	2004	U1
7551755	FotoNation Vision Limited	2004	U1
7555148	FotoNation Vision Limited	2004	U1
7558408	FotoNation Vision Limited	2004	U1
7564994	FotoNation Vision Limited	2004	U1
7324670	Toshiba	2003	U1
7155036	Sony	2001	U1
6674877	Microsoft	2000	U1
6526161	Philips	1999	U1
6792135	Microsoft	1999	U1
6301370	Eyematic Interfaces	1998	U1
5828769	Autodesk	1996	U1
5933806	Philips	1996	U2
5715325	Princeton University,Siemens	1995	U1
5754681	ATR Interpreting Telecommunications Research Laboratories	1995	U2
5497430	Physical Optics Corporation	1994	U1
5602938	NTT	1994	U2
5479570	Matsushita	1993	U2
5239594	Mitsubishi	1992	U2
5371809	Desieno; Duane D.	1992	U1
5220618	Philips	1991	U1
5285523	Nissan	1991	U3
5347613	Samsung	1991	U1
5060278	Ricoh	1990	trifurcation
5155801	Hughes Aircraft	1990	U3
4965725	Nueromedical Systems	1988	U
4760607	Machine Vision International	1986	D
4805225	State University of New York	1986	U
4809347	Hughes Aircraft	1986	D
4821333	Environmental Research Inst. of Michigan	1986	D
4653112	University of Connecticut	1985	D
4670848	Standard Systems Corporation	1985	U
4790026	USA NASA	1985	D
4593367	ITT	1984	U
4545068	Tokyo Shibaura	1983	D
4665554	Machine Vision International	1983	D
4484349	Environmental Research Institute of Michigan	1982	D
4384273	Bell Telephone Laboratories	1981	U
4395699	Environmental Research Institute of Michigan	1981	D
4400828	Bell Telephone Laboratories	1981	D
4559604	Hitachi	1981	D
4319221	Nippon Electric	1980	U
4288782	Compression Labs	1979	D
4200861	View Engineering	1978	D
4119946	National Research Development	1977	bifurcation
4014000	Hitachi	1976	S
4057845	Hitachi	1976	S
3898617	Hitachi	1974	S
3643215	Electric & Musical Industries	1968	S

Table 10: Top 20 cited patents related to video indexing patent group and their assignees.

# of citations	patent num	Pub. year	Assignees name
205	5014267	1991	Datapoint
185	5253275	1993	Browne, H. Lee
148	5666157	1997	ARC
145	5969755	1999	Texas Instruments
129	6236395	2001	Sharp Labs. of America
126	5227985	1993	University of Maryland
123	5454043	1995	Mitsubishi Electric Research Labs.
123	5774591	1998	Xerox
122	4930160	1990	Vogel; Peter S.
115	6301370	2001	Eyematic Interfaces
112	5442389	1995	AT&T
108	5835616	1998	University of Central Florida
104	4331974	1982	Iri
97	5012522	1991	The USA Air
97	5781650	1998	University of Central Florida
96	5245533	1993	A. C. Nielsen Comp.
94	5412738	1995	Istituto Trentino Di Cultura
93	5430809	1995	Sony
93	6374260	2002	Magnifi
91	5423554	1995	MetaMedia Ventures

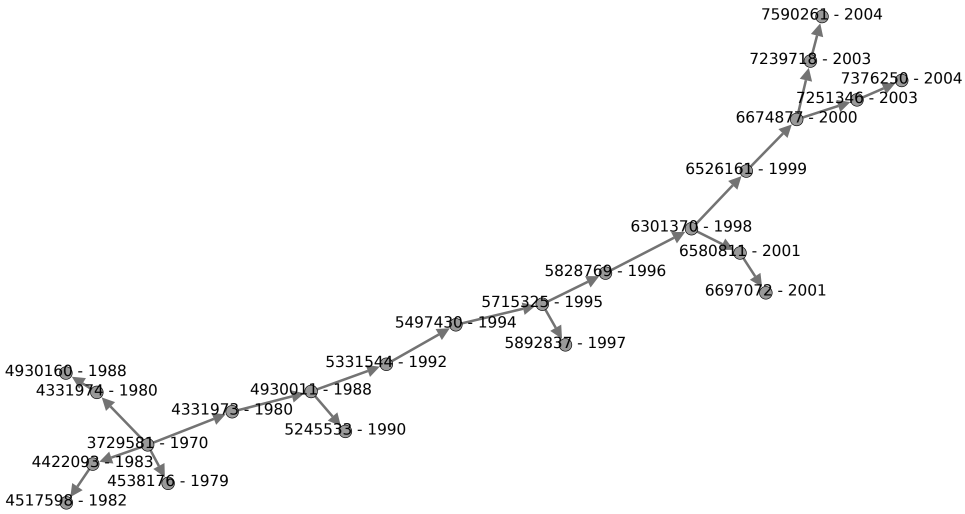

Figure 9: Network of main paths of the video indexing determined with SPNP. Nodes are labeled with publication number - application filing year.

Table 11: Firms on the network of main paths of the video indexing.

Patent num	Assignees name	Pub. year
7376250	Honda Motor Co., Ltd.	2004
7590261	VideoMining Corporation	2004
7239718	Electronics and Telecommunications Research Institute	2003
7251346	Honda Motor Co., Ltd.	2003
6580811	Eyematic Interfaces, Inc.	2001
6697072	Intel Corporation	2001
6674877	Microsoft Corporation	2000
6526161	Koninklijke Philips Electronics N.V.	1999
6301370	Eyematic Interfaces, Inc.	1998
5892837	Eastman Kodak Company	1997
5828769	Autodesk, Inc.	1996
5715325	The Trustees of Princeton University,Siemens Corporate Research, Inc.	1995
5497430	Physical Optics Corporation	1994
5331544	A. C. Nielsen Company	1992
5245533	A. C. Nielsen Company	1990
4930011	A. C. Nielsen Company	1988
4930160	Vogel; Peter S.	1988
4422093	Eeco Incorporated	1983
4517598	Van Valkenburg; George	1982
4331973	Iri, Inc.	1980
4331974	Iri, Inc.	1980
4538176	Nippon Telegraph & Telephone Public Corporation,Hitachi, Ltd.	1979
3879133	Compaagnie Electro-Mecanique	1973
3814521	Hoffmann La Roche Inc.	1972
3729581	Display Sys. Corp.	1970

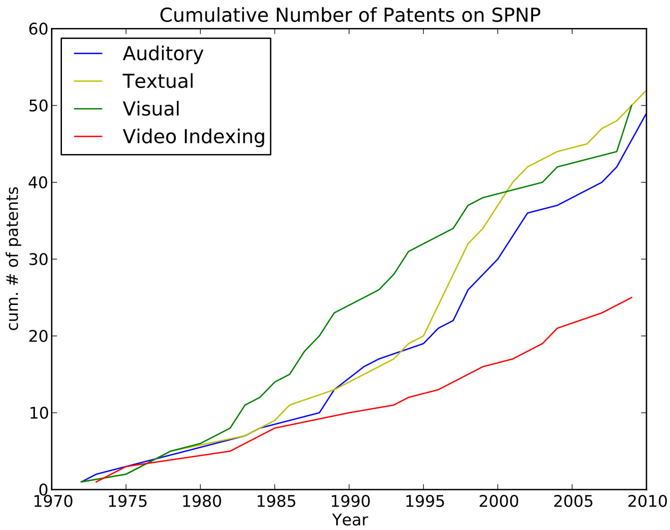

Figure 10: Yearly cumulative number of patents found on network of main paths.

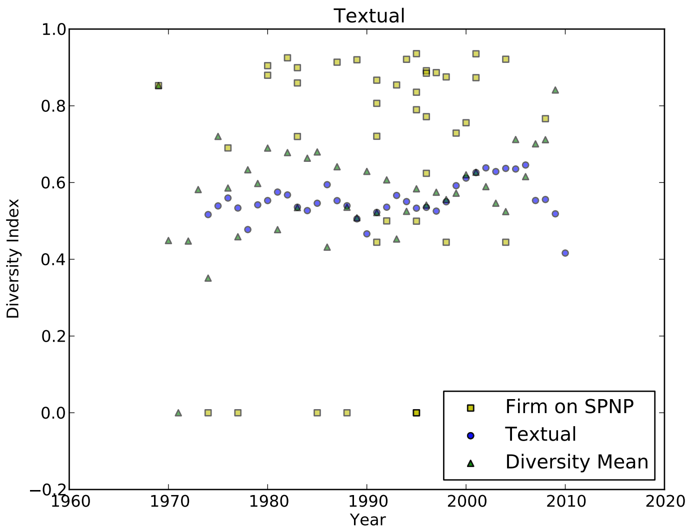

Figure 11: Diversity index of the character recognition analysis.

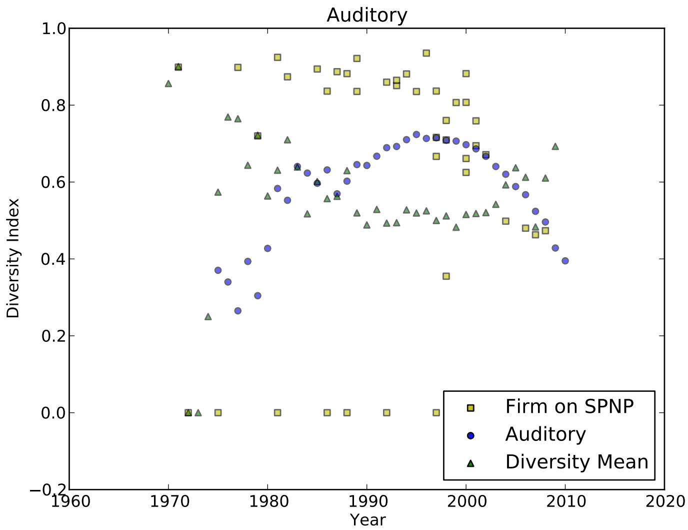

Figure 12: Diversity index of the speech/audio analysis.

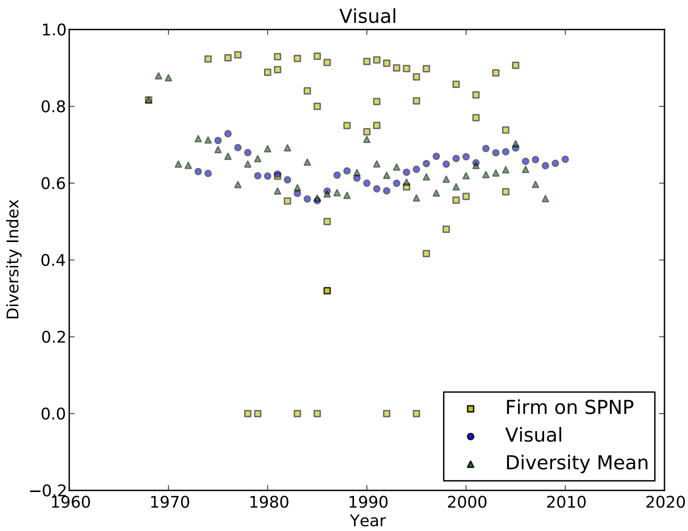

Figure 13: Diversity index of the image analysis.

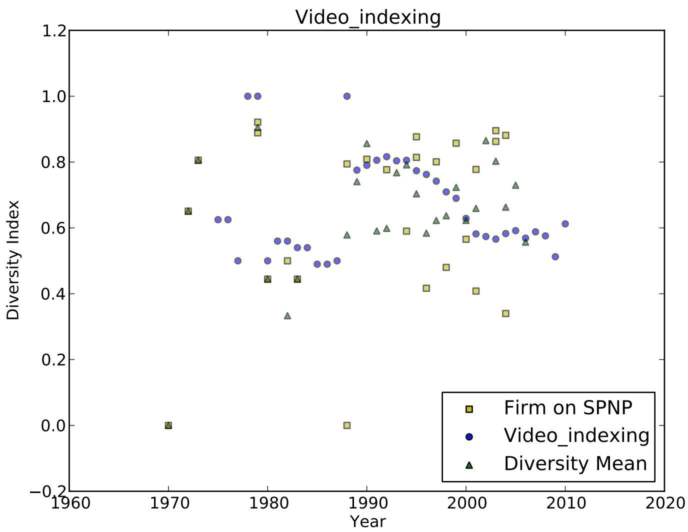

Figure 14: Diversity index of the video indexing.