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Visualizing Perspectives and Trends in Robotics based on Patent Mining

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Abstract— **Technological and fundamental developments in robotics can emerge from various sources like publications or international research plans. Among the various sources of analysis, patents results valuable in expressing the efforts performed both by companies and research institutions. This work takes the occasion of the fifty years of robotics for presenting an analysis and visualization of trends in robotics by means of patent mining. This work focuses, in particular, on the domains of rehabilitation and surgical robotics. The discussed methodology highlights the role of haptic interfaces in these fields and the relationships between relevant companies.**

I. INTRODUCTION

The field of Robotics has shown an increasing growth in recent years, extending its impact in society and opening new application areas. This field has required, since the beginning, the integration of research from different domains of science and engineering, and in recent years more and more areas impacted on robotic research like biology and neuroscience. In general, research on robotics is broad both in terms of fundamental technologies and in applied solutions, and in its being performed in parallel by companies and research institutions. While for public research institutions research topics depend on the directions given from national and international bodies, the identification of research topics and products for companies is subjected to applicability of technologies, markets and accessibility to technological solutions.

The identification of current trends in robotics is interesting; in general for understanding the major directions, and in particular it is highly relevant for research entities that want to identify which solutions have been protected by others, allowing to steer research, development, possible acquisitions and agreement strategies. Several are the solutions identifying technological trends, some are based on hints from publications, others from companies' outcomes, others from listing of international research projects and proposals . Finally another valuable source of information for the identification of trends is provided by patents being the main mechanism for protection and licensing of technological solution adopted both by companies and research institutions.

The aim of this work is indeed the identification and visualization of relevant trends in robotics, exploiting information included in patents. In particular, this work employs techniques from text and graph analysis for the identification of trends in two specific fields of robotics: surgical and rehabilitation.

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II. RESEARCH CONTEXT

The great interest in Robotics is testified by recent policies implemented at the international level for supporting further developments of the field. For instance, the European Commission since 2007 has launched a call for providing financial support to the research in the field of robotics and cognitive systems, particularly in manufacturing and services. Such financial support derives from the understanding that technical systems should be effective in upgrading their performances, especially where the dealing with humans is a requirement. The government of South Korea has promised to invest about 750 U.S. million dollars for Korean robotic industry in order to support and accelerate its growth. Recent programs and calls were launched also by other countries, such as Australia, China and United States.

Considering such a thriving research field, few studies have shown a deep interest in outlining possible trends and in mapping aspects of such technological field. Lee [1] recently performed a co-word analysis on the Korean technological project database, presenting a two-dimensional diagrams for robot technology, suggesting a feasible trend of the main topics discussed. At the same time, in U.S., an interesting study, published by the Computer Research Association (CRA), developed a roadmap on U.S. Robotics in cooperation with a wide range of businesses on robotics [2]. In Europe these analysis are receiving even more importance. The European Robotics Platform (EUROP) [3] devotes particular attention on contributing to statistics, forecasts, and foresights on Robotics preparing a report drafted by experts in the fields [4]. In parallel to these types of analysis there are efforts in describing the history of robotics [5] and specific publications on emerging technologies in robotics [6].

While the above roadmaps and historical perspectives are constructed from personal expertise and publications, there is another source of information: patents. Patents not only provide protection to technological solutions, but they only provide the fundamental and structured way of licensing technologies from research institution. Both the protection and licensing role of patents are expression of the role of these documents in describing technological innovation, and eventually subsequent market changes. Patents contain more detail concerning technology than any other scientific technical publication. Information included in patent document mainly allows decision makers to assess their technology position with respect to competitors R&D strategies, to

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recognize strategic chances and options by analyzing competitors market policies and to verify possible new alliances to be established with important market partners [7].

The approach proposed in this work follows a view of technology as an evolutionary process, in which the importance of any invention or improvement is highlighted by its role in contributing to further developments. In this line, it appears relevant that research institutions realize the value of patent information for drafting future research roadmaps by assessing patent information of a given context as part of the institution's strategic planning process, as well as the communication channel to external society.

The paper is structured as follows: first it is presented the general methodology of patent mining adopted in this work, then the two case studies on rehabilitation and surgical robotics are presented. A discussion about extension on the methodology and application in new fields concludes the last part of the paper.

III. Material and Methods

Since patent data cover the great majority of recorded inventions, this work assumes a patent as a *proxy of a technology*, and that the evolution of patents along time is a representation of technological innovation. Patent data are indeed grounded in a view of technical change as a cumulative process, whereby each innovation builds on the body of knowledge that preceded it, and forms in turn a foundation for subsequent advances. It is possible to compute the measures using detailed information contained in patents, relying heavily on citations to other patents, since these citations provide good evidence of the links between an innovation and its technological antecedents and descendants [8].

The core concept associated to patent citations is the one of technology trajectory. Dosi [9] defined a technology paradigm as *"a model and pattern of solution of selected technological problems, based on selected principles from the natural science and on selected material technologies"*. Such a paradigm is influenced by incremental innovations, but the fundamental directions in which technology may develop has already been fixed by the paradigm itself [10]. This development was identified by Dosi as *technological trajectory*.

Therefore, the *trajectory* is identified with respect to a set of possible technological directions; this means that some types of technological taxonomies have been adopted for decomposing the domain under investigation. Consequently, it is possible to consider a *technological trajectory* as a selection of the different possible ways a technology has developed to satisfy the revealed needs of the users across space and time. It can be assumed that a given innovation, belonging to a developments set of a given domain, remains present for a number of years depending on how such innovation is able to adapt the paradigm to the market needs.

A. Patent Set

This work approaches trend analysis of a given technological domain by creating a patent set allowing domain experts to identify patterns and relevant information by exploiting visualization techniques. The patent set is constructed starting from relevant domain information, as well known patents or assignees. From these few elements the patent set is constructed by means of a crawling algorithm exploring citations network (both in terms of back and received citations). This work analyses patents granted by the United States Patent and Trademark Office (USPTO), and more specifically the database provided by National Bureau of Economic Research (NBER) [11] containing the metadata of all the USPTO patents from 1975 to 2006 (NBER06: 3.4 millions patents and 23.6 millions citations).

B. Classes

In order to apply for a patent, whether at national or international level, whichever actor interested in has to determine specific aspects of its innovation, i.e. the newness of the creation, the title to property, its main characteristics. To determine these features, huge amounts of information must be searched. In order to keep them up to date, they are continuously revised by committee of experts, and new versions are regularly published. The patent classification systems intellectually organize the large quantity of patents into predefined technology classes. Considering the diversity of technological fields, a patent may be classified with more than one class [12]. The USPC aims at organizing all the U.S. patent documents into classifications based on common subject matter. Each subject matter comprises a major component named a class which differentiates technologies, and a secondary component named a subclass which delineates functional features of the subject matter encompassed within the scope of a class. Specifically, the first number is the class of patent, that for utility patents, ranges from 1 to 999, while the second is the subclass depending on the class number. At the moment there are about 450 classes, some of them are grouped (i.e. Surgery 600-607 and Data Processing 700-707) while others are quite isolated (i.e. Robots 901).

The distribution of classification information in the patent set can be analyzed and presented adopting a visual mapping operation that allows to compare changes in classification both along time and respect different patent set. The solution proposed in this work is based on a mapping operation that maps the values of the classification into fixed coordinates over a map maintaining the conceptual vicinity of classes near each others. In particular, we are proposing to adopt a space filling curve for generating a constant mapping between USPC codes and a two dimensional coordinate. The specific curve adopted is the Hilbert Curve [13] that has the interesting property to keep sequential elements spatially near, providing an automatic mapping of the grouping of the class sequences from USPC. This solution is quite different with respect to the Treemap approach [14] that requires the identification of a hierarchical structure with respect to the classes, and also modifies the positioning of the entities with respect to their relative size. More specifically the Hilbert Curve is a continuous fractal space filling curve that can be recursively generated and at the step n the curve has a length of $\left(2^n - \frac{1}{2^n}\right)$.

C. Assignees

The NBER data has a specific focus on assignees; assignees have indeed been subjected to a normalization process integrating information from the Standard & Poor's Compustat database of companies. By means of this list and specific text matching functions allowing to manage common misspelling, it is possible to replace the assignee textual field with an index representation. In particular, NBER06 uses a list of about 220k assignees. The assignee of a patent is indicated in the patent document in the form of a list of people or a single institution that has the legal rights over a given patent. This data need to be parsed for extracting useful information. Since most of the research is performed by industries or research institutions, the assignees analysis will be performed within one of these two categories, discarding single inventors/assignees. The resulting data set allows in this way to describe roles of assignees and their relative interactions.

D. Citations

Citations analysis allows to create a Citation Network represented in the form of a citation graph in which nodes are patents and arcs are citations. This graph is a directed graph with no weights that is, by definition, not looping except when there are issues in the dataset. We can assume for the rest of the discussion that it is a direct acyclic graph, and this is a feature that makes the patent citation network different with respect to Bibliometric and Web networks.

The Citation Network can be analyzed in terms of flow of information from cited patents to citing patents. This interpretation is highly relevant in patent analysis since this flow is part of the review process and the declaration of novelty of a patent. In the citation graph G there are two nodes that are interesting in terms of information flow: sources and sinks. A *source* is a patent from which only information flows into, in the sense that incoming information is provided by external sources or patents not in the patent set, while a *sink* is conversely a patent in which information enters only.

A measure of flow for a Citation Network has been developed by Hummon [15] that introduced several types of weights for modeling citations in publications related to DNA. Among these weights, the Single Path Link Count (hereafter SPLC) is the most famous involving the measurement of the number of paths that connect one node to all the others. As shown by Batagelj [16], the SPLC algorithm is an exponential algorithm that can be replaced by a more efficient and intuitive algorithm that is the Single Path Count (hereafter SPC). The SPC algorithm considers instead the number of paths from all the sources to all the sinks. By exploiting the fact that the graph is acyclic, this algorithm has linear complexity and it provides a measurement that is associated to the flow of information along arcs. In particular, it is possible to show that such algorithm has a property equivalent to the Kirchoff law for electrical circuits: the sum of the incoming flow of information is the same as the outgoing flow. The weight w_{ij} computed by SPC measures the information flow from node i to j and it states that:

$$w_i = \sum_{j \in p_i^{OUT}} w_{ij} = \sum_{j \in p_i^{IN}} w_{ji} \qquad (1)$$

Trajectories can be identified inside the components by constructing the path starting from sources with the highest information flow, and following the most relevant patents identified by means of the SPC weight. In particular, it is discussed a trajectory computed by means of the heuristic algorithm that identifies the chain of the most relevant patents starting from sources and following the most relevant information flow.

In addition from a generic citation network, it is possible to derive a co-citation network that puts into relationship specific categories of information, like Co-Classes, Co-Assignee or Co-Citation of patents.

E. Trajectory Analysis

The Citation Network can be used in conjunction with the publication dates to understand the distribution of the difference in citation time with respect to citing and cited patents, and this information can be used for understanding the relevance of a patent with respect to the whole set. In particular, patents will be classified depending on their in-citation profile along time. For a given patent i the in-citation profile is defined as:

$$p_i^{IN}(t) = || \left\{ j \in p_i^{IN} | p_j^{PUB} - p_i^{PUB} = t \right\} ||$$

In the above expression, the time t, expressed in years, is upper bounded by the time limit of the patent database, reduced by the mean lag time, that means for the NBER06 to be centered in 2003. We identify this limit as T_i^{IN}. The patent classification by in-citation profile is obtained by taking the profiles over a period of 15 years, motivated by number of available patents and typical technology importance, and identifying the different behaviors along time. The patents to be analyzed are taken from the patent set, but the p_i^{IN} is computed with respect to the whole patent database. This choice is motivated by the way the patent set has been constructed; in particular, the p_i^{IN} computed over the patent set has the same value of the one computed over the whole database for all patents, except those patents reached in the last iteration of the expansion procedure.

The identification of behaviors is obtained by clustering the in-citation profiles using the K-Means algorithm, with a distance function that is appropriate for sequential data (sample correlation between points). The K in the algorithm has been set by looking at the distribution of the patents and the relative silhouette. The result of the clustering gives the label of every patent and a centroid that is a prototype of the sequences in the cluster. This classification has been applied to a reference set of patents from robotics allowing to identify four behaviors of patents. The first cluster represents patents having an initial citation importance that after few years decreases. The second and the third clusters show a more interesting behavior representing patents that increase their importance after eight - ten years from their publication, and then they stopped to be relevant. Finally, the fourth cluster corresponds to patents that can be considered as structural ones and they are increasingly cited. For example in the last cluster, it is possible to find an interesting patent i.e. US4791934 entitled *Computer tomography assisted stereotactic surgery system and method*.

F. Implementation

The discussed methodology has been implemented in a library for patent acquisition and analysis based on Python and MATLAB. The former manages the extraction and crawling of the NBER dataset, while the latter is adopted for performing most of the graph related algorithms. For managing the size of the citation graph some parts have been optimized using C++ and the MatlabBGL library, respectively. In particular the transformation of the NBER dataset into an efficient memory mapped representation has proven to be effective respect the use of a relational database.

The crawling algorithm starts from a set of assignees A^0 and a set of patents P^0 manually collected, and from them constructs an initial patent set P^1. Then the crawler performs an iterative search of all the citing and cited patents of the P^{i-1} in NBER building at every step a new set P^i. The search is stopped when a given number of iterations or a total number of patent has been reached. Finally the assignees of all the selected patents are being retreived.

IV. Case Study on Rehabilitation Robotics

Rehabilitation Engineering refers to the systematic application of engineering sciences whose mission is to improve the potential of people with disabilities through the use of technology. It incorporates two important branches: rehabilitation robotics and assistive robotics.

Rehabilitation Robotics is a branch of robotics that aims at providing technologies and solutions that can help people to recover from trauma, typically after stroke or other neuromotor disorders. Its main target is to investigate possible applications of robotics to therapeutic procedures for achieving improvements in motor and cognitive functional recovery. Currently, several robotic systems are successfully providing physical and occupational therapy, intensifying the treatment providing a better convalescence and rehabilitation if compared with conventional approaches.

Due to these specific characteristics, the field of Rehabilitation Robotics needs to be differentiated with respect to Assistive Robotics. The goal of Assistive Robotics is indeed more focused on developing robotic aids for people with physical disabilities who have chronic or degenerative limitations in motor and cognitive abilities.

It is worth to mention that although such important differences, for a while, since the beginning of the '70s, the field of Rehabilitation Robotics was considered almost equivalent to the Assistive Robotics. As matter of fact, Dallway, in providing an overview of Rehabilitation Robotics in Europe with its historical background, used the term Rehabilitation Robotics for indicating assistive solutions [17]. Following the same line of considerations, Hillman, in one of his studies, provides a quite clear historical perspective of the Rehabilitation Robotics field counting assistive robots (i.e. fixed site robots, powered feeding devices, mobile assisted robots, or orthotics) as rehabilitation aids [18].

Recent discussions about directions of Rehabilitation Robotics have been performed in different studies [19] and [20]. In addition, further contributions give a systematic review of studies that investigate the effects of robot-assisted therapy on motor and functional recovery in patients with stroke [21], and other ones investigated how robot-aided therapy appears to improve motor control more than conventional therapy [22],[23].

From a technological point of view, the current interpretation of Rehabilitation Robotics term, conceived as machines that can be used to help people to recover from severe physical trauma, is motivated by a stronger role of haptic interfaces that allow to control in a better way the action of the human and the robot while providing the therapy [24].

Notwithstanding the fervent research on this topic, several questions are still to be provided. Does this research area have the potentialities for offering an effective growth along the forthcoming years? Have the contribution of haptic technologies pushed and supported such growth? Which are the main technological components considered as fundamental in this field?

The main purpose of the following sections is to provide insights and considerations for contributing in this context, defining and predicting trends exploiting patent information.

According to the methodology proposed above, the first step is the construction of the patent set. The creation of the patent set initially starts with the identification of well-known patents related to products or systems already commercialized. Once having identified the main products, it is important the identification of the related assignee, i.e. companies, which may have filled further patents relevant for the topic discussed.

Considering the relevant contributions, the commercial solutions already available on the topic, and the previous knowledge, the following systems have been identified as starting points:

- MIT-Manus (commercialized as InMotion) - Massachusetts Institute of Technology
- Rutgers Master - Rutgers University
- Lokomat - Hocoma

In the case of the Massachusetts Institute of Technology (MIT), it is not possible to contribute to the construction of the patent set considering the assignee's portfolio, due to the extensive number of patents in different research fields. The MIT indeed includes research units and laboratories from different fields. Past achievements include for instance, the first chemical synthesis of penicillin and vitamin A, the development of inertial guidance systems, modern technologies for artificial limbs or high speed photography. Therefore, since it is not feasible to consider the whole MIT's patent portfolio, a fundamental patent of the Institute in the

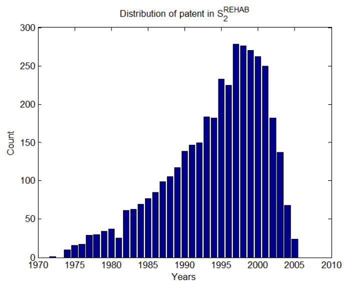

Fig. 1. Patent Set distribution along time

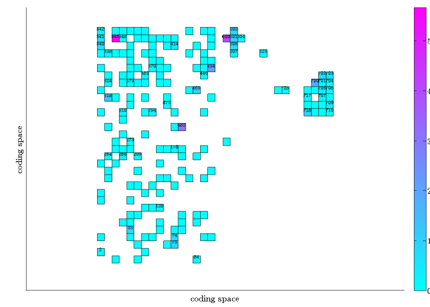

Fig. 2. Patent classification map of S^{REHAB} based on the Hilbert Curve. In the map it is interesting to identify the area of Surgical (600-606) in top center, the control systems and data processing (700-715) in top right, exercising device (482) in the middle, education and demonstration (434) in the upper center, and display (345) in top left.

field of Rehabilitation Robotics, i.e. the MIT Manus patent ("Interactive robotic therapist" US5466213), is considered as an initial input. Such a robotic device has been designed and programmed for clinical neurological applications, and has undergone extensive clinical trials for several years in different hospitals providing positive benefits [23]. Due to its importance and relevancy, such a patent allows to identify immediately a whole set of associated patents and assignees.

The same considerations can be extended to the Rutgers University as an assignee and its main result, i.e. Rutgers Master patent ("Actuator system for providing force feedback to a dextrous master glove" US5143505).

As far as the Hocoma is concerned, considering its role in robotic rehabilitation therapy for neurological movement disorders, it is feasible to consider the whole innovative therapy solutions developed, starting from one of its main products, i.e. Lokomat patent ("Device and method for automating treadmill therapy", US845360).

By taking into considerations the above initial elements, the Patent Set has been created using the NBER06 database. Once having identified the initial elements, the second phase deals with the progression of the elements' expansion that could be performed in subsequent steps: 4 elements as input, 286 elements at the first step and 3589 elements at the second step. The resulting Patent Set is composed by a total amount of 3879 patents, of which 2531 patents (around the 65% of the set) are identified with a known assignee. Such a set hereafter will be identified as S^{REHAB} . Figure 1 shows the time distribution of this patent set. The class distribution of this set can be presented using the Hilbert map discussed above, allowing to identify the most relevant classes as shown in Figure 2. Finally the application of the Trajectory identification algorithms is shown in figure 6, in which the fundamental structure of the main trajectory has been annotated by relevant topics of the patents in the branch.

V. Case Study on Surgical Robotics

Although it has been over 15 years since the first introduction of a robot in surgical procedures, the field of Surgical Robotics is still emerging, and it has not yet reached a critical mass [25]. With the experience and knowledge gained from the systems already in use, acceptance of surgical robots is in general growing.

The use of robotics as part of a computer-integrated surgery system helps to improve accurate and targeted medical interventions. It has been recognized that surgery will be affected by the integration of computers and robotics much more than the manufacturing field was revolutionized by automation several decades ago [2]. The area of Surgical Robotics has a different and longer story with respect to Robotics Rehabilitation.

This area is broader both in terms of applications and technological solutions: the number of operations requiring technical improvements methods is increasing, and consequently new procedures and technologies are being investigated.

Among the different surgical robots, it is possible to find different types from teleoperated to shared control robots. Taylor classified the main areas for surgical assistance in the following [26]:

- assistance functions robots
- telesurgical instruments
- navigation system
- robots for precise positioning
- robots for specific surgery tasks

Apart from the specific application fields of surgical robotics the main distinction in terms of applications is among Open Surgery (OS) and Minimally Invasive Surgery (MIS). The former deals with the cutting of skin and tissues that can be seen and touched by the surgeon and exposed to the air of the operating room, while the latter refers to surgical procedures that do not require large incisions. It is in this second case that the surgeon requires the involvement of specific tools and aids able to offer better techniques allowing the patient to recover faster and with less pain.

Several works review the history, development, and current applications of robotics in surgery. Lanfranco [27] for instance, undertakes a review of the literature using Medline, identifying articles describing the development of surgical robots reporting data on applications. He states that Robotic Surgery is still in its infancy, and its niche of applications has not yet been well defined. Following the same line of reasoning, Narula and Cepolina, in separate studies, investigated the development of robotic surgical systems and instrumentation, identifying the benefits they offer over

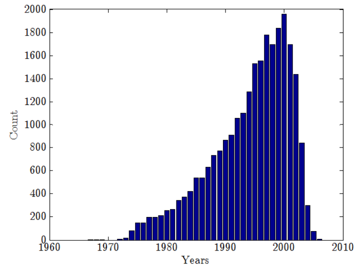

Fig. 3. Distribution $S^{SURGICAL}$ of Patent Set along time

conventional laparoscopic surgery, and the future of robotic technology [28], [29].

Two further studies of Sutcliffe [30] and Nathoo [31] provide extremely interesting considerations on the field summarizing the major contributions of the use of robots in surgery and neurosurgery respectively.

A. Patent Set

As done for the Rehabilitation Robotics case study, the starting point of the analysis is the Patent Set construction. Such a creation initially starts with the identification of well known companies (assignees) that have a strong and focused role in this field. Considering the relevant contributions, the commercial solutions already available on the topic, the following major actors have been identified:

- Intuitive Surgical, Inc.
- Computer Motion
- Stereotaxis
- Hansen Medical, Inc.
- Prosurgics Ltd

After having identified the initial elements, the second phase deals with the progression of the elements' expansion performed in subsequent steps: 129 patents as input,1318 patents at first step,24347 patents at second step.

The resulting Patent Set is composed by a total amount of 25794 patents, of which 19203 (around the 74% of the set) are identified with a known assignee. This set hereafter will be identified as $S^{SURGICAL}$. The resulting distribution of the Patent Set is shown in Figure 3. The analysis of the patent set in terms of classes gives interesting information, that can be easily presented using the Hilbert 2D map discussed above as shown in 4.

B. Trajectories

The next step in the analysis of the Surgical Robotic field is the identification of effective trajectories along time, that correspond to discover relevant time series. What can be understood from the analysis of the patents over this main path is that, patents are more related to fundamental technologies for surgery than to specific robotic capabilities. The reason is that most of robotic technologies in this field make use of these grounding innovation.

For this reason is interesting to study how different assignees change their role along time. In particular it could be interesting to verify if the co-citation pattern between

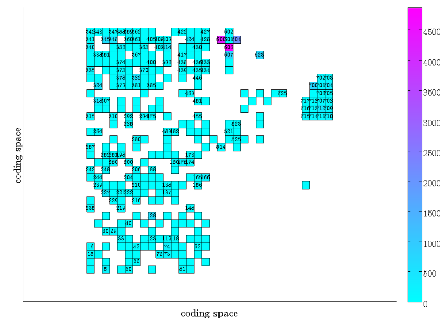

Fig. 4. Patent classification map of $S^{SURGICAL}$ based on the Hilbert Curve. Clearly there is a very strong focus on the Surgical classes and in particular 606. In addition to computer processing for control (700) and display (345) there is a strong presence of imaging techniques (378 and 382).

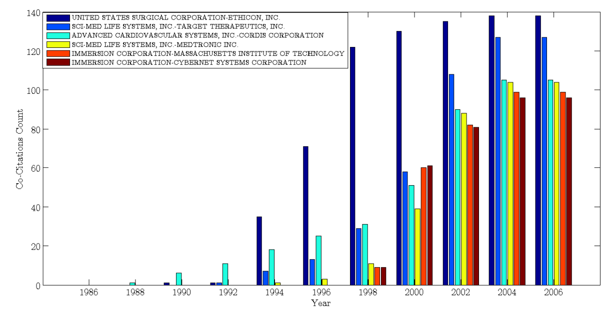

Fig. 5. Main relationships between assignees from the co-citation analysis in $S^{SURGICAL}$. These associations allow to identify possible relationships at the level of companies like agreements or acquisitions

assignees can provide some insights related to changes in the relationships between assignees, like acquisitions, mergers or agreements. The six strongest connections among assignees in the last period of the patent set are illustrated in Figure 5 after the removal of self citations.

In particular the interesting co-citations are:

- Immersion cites Cybernet Systems from 1998. In 1999 Immersion acquired Cybernet Haptic Systems
- Advanced Cardiovascular Systems cites Cordis from 1988 are the same company
- Heartport cites Stanford Surgical Technologies from 1996. The latter was the original name of the same company founded in 1991.

C. Trends

When considering the patents in the set $S^{SURGICAL}$ over the last 5 years (from 2000 to 2006), the classification of the patents based on in-citations time profiles provides a group of promising patents. Such patents have a profile which shows a growing interest by matching the profile. Finally, the patents in this group, that are most relevant for the forthcoming surgical robotic developments, are the following:

- US6149583 Device and method for isolating a surgical site held by Heartport (highly relevant)

- Various haptics patents by Immersion associated to medical imaging (e.g. US6088019)
- Improvements of Sensable's Phantom and other haptics (e.g. US6084587)
- Multiple patents on coronary bypass with associated tools (e.g. US6093166)

These starting points can be used for constructing an interactive 3D map of the relevant trends shown in Figure 7.

VI. Main Conclusions

This paper has introduced a methodology for the analysis of trends in technological fields by means of patent analysis, providing specific examples related to two areas of robotics. Several are the directions that can be implemented by this work. From one side there is the capability of covering larger areas of a domain, as the whole robotic field, on the other the possibility of taking into account newer advancement in the field by means of the patent application analysis. The opportunities for investigating the relationship between assignees in order to highlight trends and patenting behaviors are interesting as well. Additional information can be obtained at `http://www.percro.org/project/patlib/`.

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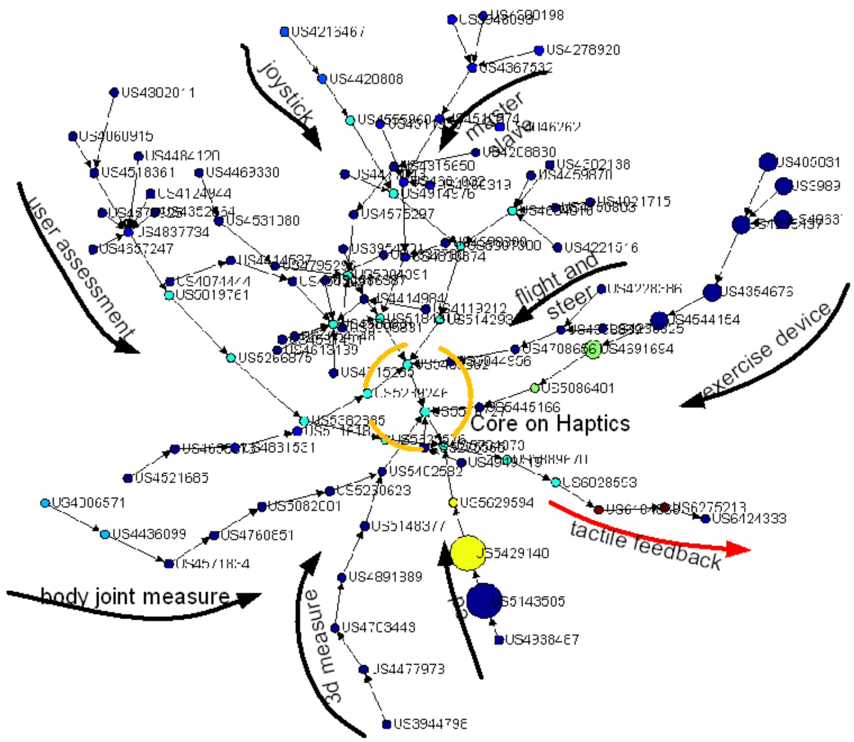

Fig. 6. Main trajectory of the Patent Set and annotations about relevant topics

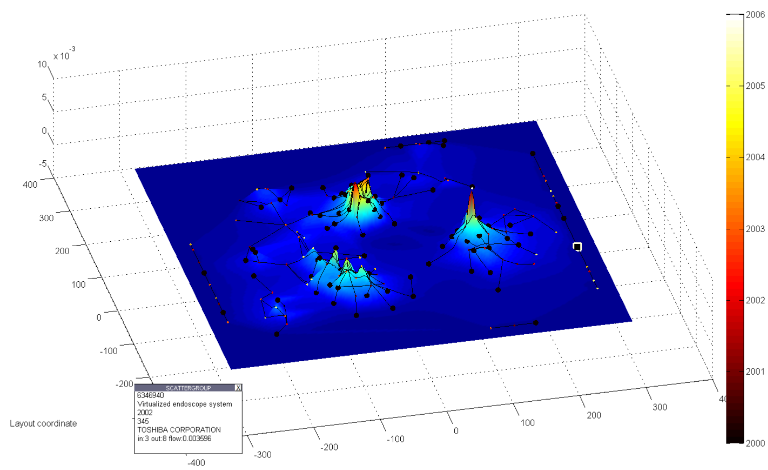

Fig. 7. Trends of the Patent Set identified as trajectories starting from the key patents. The key patents with promising profile are highlighted with bigger marks, while the trajectories hold patents colored differently depending on the year. The interactive interface allows to highlight details about single patents.