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AI based Patent analyzer for suggesting solutive actions and graphical triggers during problem solving

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Abstract. This paper proposes an idea for developing a computational model of creative processes in design. This model facilitates and accelerates idea generation in the inventive design, increasing the solution space definition by suggesting technical actions and graphical triggers.

The problem solver has to state the required design objective using any verbal action, then an automatic system generates an appropriate set of triggering actions indicating different ways of accomplishing that goal. In addition, for each verb is associated a list of evocative images indicating how that action can be implemented in space/time and through specific physical effects. The system is capable of handling the huge number of verbs that the English language offers. To select all functional verbs of the technical lexicon, the patent database has been processed using the most advanced text mining techniques. Among them, a customized version of Word2Vec model has been exploited to learn word/actions associations from a large corpus of patents.

The article explains how the libraries have been created, the progress the software prototype and the results of a first validation campaign.

Keywords: CAI - Computer aided inventing, Cosine similarity, problem solving, creative trigger, TRIZ, AI.

1 Introduction

Creative processes in computer-aided design are identified as those that introduce new design variables into the design process. In TRIZ, variables are usually associated to new resources helping designer to go out of routine design towards a design space extended.

But how can these resources be suggested during the problem-solving phase? TRIZ experts are used to cross-fertilize different tools to accurately scan the problem space: they use abstraction, continuous problem reformulations in functional/temporal/spatial terms, decomposition in sub-problems at different levels of detail up to the identification of the technical parameters that control the contradictions.

Attempts to replicate this model using CAI (computer aided inventing) system are very topical, just think of semantic engines for functional search and physical effects [1-3], proposals for integrating semantics and case-based reasoning CBR [4], morphological matrix [5-6], Information retrieval by artificial intelligence [7], up to the latest thinking machines for writing patents [8]. But to date we can say that we are still far from replicating human reasoning. Although very different all of them have in common the choice of patents as knowledge sources and the use of text mining tools to extract key technical concepts from them. The advent of new natural language processing algorithms, word and sentence embeddings, and pre-trained language models such as BERT (Bidirectional Encoder Representations from Transformers) [9] has accelerated a race toward new paradigms of CAI computer aided inventing that has origins far back in time.

This article is part of this series of attempts. Its purpose is suggesting ideas, in form of a combination of actions and related images helping to adapt the verb to the specific context. This simplified approach, although it cannot replicate the complexity of a methodological path such as TRIZ, has the advantage that it can also be used by nonexperts in problem solving. Chapter 2 shows the state of the art of tools for CAI development. In Chapter 3, the construction of the language library is explained to suggest other ways to functionally address the high-level problem. The graphical triggering mechanism is instead introduced in chapter 4. This is followed by the results of a validation campaign and a final chapter on the progress of the work and future developments.

2 State of art

Solving a problem by suggesting the good action is not a novelty. The literature counts numerous methodological approaches based on the systematic use of verbal forms, pointer to effects, Inventive Principles, Function Oriented Search, Matchem-ib [10], Scamper [11], functional basis by Nist [12] and other forms of cataloguing typical of linguists studying the English verb lexicon.

Theoretical methods are supported by information technology to make the most of the technical knowledge base, especially patent knowledge that is widely used in the TRIZ community. The pioneer of all CAI software was Goldfire Innovator [1], that in the early 2000s showed the potential of a SAO-based (subject–action–object) text mining techniques for implementing FOS approach. Goldfire's most important limitations were that it worked almost exclusively on SAO triads, and that it had problems handling the Object if it appeared as complex multiwords. Today we know that the use of SAOs alone is very limiting [13], in spite of other linguistic forms that are more common in the English language (e.g. for $+$...ing, to $+$...inf).

Luckily, research on natural language processing has made big leaps forward in the last years, thanks to projects such as IBM Watson [14], GPT-3 by OpenAI [15], BERT by Google [9], and open-source word embedding models like Word2Vec, GloVe, FastAI. These advancements, matched to a cloud computing environment, have allowed the processing of huge corpora in a reasonable computing time.

The only drawback of these models is the fact that they are trained on general-purpose datasets (Wikipedia, BookCorpus, etc), and they lack knowledge of technical and patent lexical terms.

Although important steps have been made [16], automatic technology features recognition is still an open problem in order to well understand technical content.

Automatic technology features recognition is still an open problem in order to well understand technical content.

In this work, the ability to automatically recognize the function of a component described within a patent text is crucial. The software system has to work real time on a corpus of many millions of documents without any form of limitation.

Thanks to this innovative technology developed by the start-up TRIX it was possible to develop the verb libraries described in more detail in the next chapter.

3 How to create a problem-solving actions library

The English language has more than one million terms, of which about 10% are verbal predicates, approximately just over 100,000 terms. Among these, an important number that is impossible to estimate is represented by functional verbs, i.e. useful in problem solving to suggest a solution.

To identify this set of relevant verbs there are no ready-made text mining tools in the literature. It was therefore necessary to start from a manual classification of verb forms. Two different models of classification were taken as reference: the Functional basis of NIST and the classification proposed by Beth Levin [17].

3.1 Functional basis

Functional basis has been conceived to support functional basis of an artifact. It is a collection of functional verbs hierarchically organized into categories according to their level of generality. Inspired by the modelling of Paul & Beitz, Functional basis has been subject to improvements by many authors until its version "Functional basis reconciled", which includes the NIST taxonomy [12]. The final result is a model characterized by 3 levels of classification and a list of correlated verbs as shown in figure below. In each category the list of verbs is exclusive to eliminate ambiguity.

Class (Primary)	Secondary	Tertiary	Correspondents
Branch	Separate		Isolate, sever, disjoin
		Divide	Detach, isolate, release, sort, split, disconnect, subtract
		Extract	Refine, filter, purify, percolate, strain, clear
		Remove	Cut, drill, lathe, polish, sand
	Distribute		Diffuse, dispel, disperse, dissipate, diverge, scatter
Channel	Import		Form entrance, allow, input, capture
	Export		Dispose, eject, emit, empty, remove, destroy, eliminate
	Transfer		Carry, deliver
		Transport	Advance, lift, move

Fig. 1. Functional basis reconciled by Nist.

The total number of verbs belonging to this classification is about 50 divided into 8 macro categories. The corresponding verbs that can be associated with these categories unfortunately do not exceed 200.

3.2 Beth Levin classification

Beth Levin is an American linguist and Professor in the Humanities at Stanford University who conducts her research on the English language and its lexicon [17]. Her recent work investigates the representation of events and the ways in which events and their participants are expressed in English. Those studies necessitate the development of verbal meaning models, since verbs are the main element used to describe events.

She proposes a classification of over 3 thousand verbs, grouped according to their "diathesis alternations" and into classes of actions with similar meanings. It counts 58 classes, typically with about five subclasses. The guiding principle is semantics first, syntax second; so, for example, a class of near-synonyms may be divided according to whether or not it allows a certain diathesis alternation. Verbal forms have no connection to the more technical world of engineering and problem solving, but they are a great starting point for excluding non-functional ones and exploring the others.

Unlike functional basis, a single class can contain many more verbs, and individual verbs can repeat in multiple categories since they can have different meanings.

An example of a class is "funnel" verbs, consisting of: bang, channel, dip, dump, hammer, ladle, pound, push, rake, ram, scoop, scrape, shake, shovel, siphon, spoon, squash, squeeze, squish, sweep, tuck, wad, wedge, wipe, wring.

Again, the greatest limitation of this approach is the limited sample compared to the total number of verbs present in the English language. The verbs already classified and related to the technical sphere are little more than a hundred.

3.3 Building our own Patent based Library

In order to implement the system to generate suggestions, it was necessary to create a new library of functional verbs, much richer than those seen so far in the literature. The first step was to put together the work already described in the previous paragraphs. The system architecturis outlined in the figure 2 and is composed of multiple actors like cloud functions and operations, virtual machines and elasticsearch databases. The cloud

Fig. 2. Overall architecture

infrastructure leverages the Google Cloud Platform (GCP) system and the python language has been used in all stages of development.

The verbs found were organized according to a very simple 2-level hierarchy: a generic verb represented by a whole category and a list of verbs associated with it. Generic verbs are unique, while verbs included in the second level can appear several times in different categories. Compared to previous work, the functional verbs associated with the second level are much more numerous, to date just over 2 thousand terms have already been validated. Each of these verbs was then expanded in turn semantically using its own network of lexical resources by using synonyms, troponyms, iperonyms.

This approach allowed us an initial level of pool expansion that was notable greater than previous approaches, but still limited in comparison to the ultimate goal. The biggest problem is the limitations in the available semantic network libraries, which are designed for general purpose languages and almost never for the technical lexicon.

In order to complete the work and to guarantee the total coverage of the verbal forms compatible with the problem solving, it was decided to extract the most specific verbal forms directly from the patent corpus. Currently, our patent libraries contain over 120 million documents, all digitized and translated into English. These documents were obtained from one of the largest accurate patent database through the use of a commercial api; the api provides the data in a structured json format with logically segmented fields like textual sections, images, bibliographical information.

Each patent necessarily contains a description of the starting problem, the solution and a description of how it should work. The patent pool is semantically very rich and contains the technical vocabulary typical of every technological area known to date without exception.

To identify the verbal forms contained in the corpus we used an algorithm that combines part-of-speech tagging and word embeddings. Initially, all the words in the text have been tagged with their part-of-speech function (verb, noun, etc); then, a word embedding model (Word2Vec) has been trained using the text of the words and their partof-speech as a training feature.

Word embeddings model are a type of neural network that maps words to a vector space of fixed dimension (in this case 1024), they learn vector positions through training on big textual corpus. Once the training is done, it's possible to find related words by computing the distance among their vector. The most common technique to compute those distances is cosine similarity [18].

In the specific case presented in this paper, as the model has been trained on the patent domain, it allows for better precision and reliability in a technical problem-solving. Furthermore, using the part-of-speech as a feature allows precise searches for similar or correlated actions.

At this point, for each functional verb contained in the corpus it is possible to calculate a distance with respect to the reference verbs already identified in the library; moreover, for each suggested verb there is a list of further verbs that are close to it in meaning, therefore potentially useful as further suggestions.

In this way the system is able to suggest solutions independently from the proposed verbal target, in spite of the infinite complexity of the English language. As the number of verbs with which the base library is populated increases, the level of precision of the system itself increases.

3.4 How to use a verbal Library

Any verb can be used as a problem-solving trigger, but to be effective it needs contextualization to the specific case study. If we initially choose a very specific verb, e.g., "*to weld*", the creative step that is required for its implementation will be more restrained than with a verb that is broader in meaning, such as the verb "*to join*".

There are in fact many different ways in which I can join an object, not only s*oldering* but for example also *gluing or embedding*.

Greater generality tends to create more associations between alternative verbs, conversely, specificity of meaning reduces associations but facilitates its application to the problem. The most specific situation is when we choose a verb that already contains a physical effect in its meaning (e.g. f*reezing*).

One last case that might occur is the extreme case of a too generic verb (e.g. *ameliorate, improve, increase, decrease, maintain,* etc.); these verbs alone are not useful to indicate a solution direction but if coupled with a technical parameter (e.g. increase the thickness) they are really effective. The way to treat this last category of verbs is postponed to future publications.

The proposed method requires the user to make a minimal effort: only to indicate a verb describing the objective to be achieved or the action that is thought to be useful for solving the problem (for example I want to *remove* limestone or I already decided to mechanically *break* it). The task of the library is to broaden the concept and allow navigation by functional verbs, used in patents in similar ways. Each suggested verb, in order to be used appropriately, needs its contextualization to the specific case study. The way the authors have chosen to aid in its implementation is to pair it with imagery.

4 How to create a graphical triggers library

For each verbal form described in the previous chapter, the system must return a predefined set of images. The images have been manually collected. They come from a direct interpretation of TRIZ approach and are conceived to work also with those who have no experience in problem solving.

Not being able to create images for all the thousands of verbs potentially useful for problem solving, a subset of preferential verbs was chosen, covering the first hierarchical level of the classification and over. Verbs with a similar meaning will refer to the same set of images.

The main difficulty in the compilation of this library consists in providing images capable of stimulating creativity. Therefore, the choice of images cannot be random but follows precise rules.

4.1 Rules for creating images

Although the library of images was created by hand, the process by which they were identified followed strict rules:

- 1. *By Physical effects*. Each action can be carried out through different physical effects. The first step will be to find images of applications of that function associated with a physical principle that is well recognizable. If the image alone is not enough evocative, or the effect is too hidden, it is possible to associate it with a very brief description at the bottom. Considering the verb *to shake* for example, I can find images about sound waves that shatter glass (Acoustic effect), shaker of olive trees (mechanical effect) or wind that makes bridges oscillate (resonance effect).
- 2. *By Space-mode*. A further selection criterion concerns the ways in which action can be implemented by considering the operating space. These include Inside/Outside, Above/Below, High/Low, Independent/Part of a process.
- 3. *By Time-mode.* Similarly, the operational time of the action is considered: full time/partial, slow/fast, absence or presence, dynamic or static, repetitive or not, involuntary/voluntary effect, autonomous or with intervention, ordered or random.
- 4. *By detail level*. The size scale is then considered: macro/micro, oversized or undersized, changes of state (liquid, solid, gaseous), quantity.
- 5. *By other criteria.* Whether involves other actions or if it is an isolated, level of precision, multifunction.

4.2 Prototype - SW implementation

The technology that allows the navigation of functional verbs with the possibility of associating any verb with a set of images can have many applications. Even just in the field of problem solving, it can be implemented in different ways. To date, the implementation phase of this technology has included the creation of a user interface with the sole objective of supporting an experimental campaign to test the effectiveness of the methodology. Given a problem, the user enters a verb describing the goal to be achieved and the system automatically get back a list of related actions. From here the user can choose one of the suggested actions or enter a new one resulting from the verbal stimulus action. We can go on iteratively until we come across a new verb that convinces us of its effectiveness. When the desired action has been chosen, the system will generate a set of images and the short list of related actions from which the starting one was drawn.

If an image evokes a solution, it can be easily uploaded to the system by clicking on the triggering image and writing a free-form text in the form created for it. Being able to record every user action allows developers to make analytics, monitor which paths statistically (graphical and verbal) are most followed, how many iterations are made before fixing a response.

Fig. 2. User interface of the software prototype. In the picture a partial list of the images for "Cleaning" actions and in the right top of the page the actions list of near-actions.

5 Evaluation

The stated objective of this method is to give hints to enlarge the number of the practicable ways and increase the variety of solutions in terms of physical domains. The effectiveness of graphic activators has been tested with over than 100 first year engineering management students and 40 students at the last year of academic course in mechanical engineering with a mechatronic specialization who followed the TRIZ course). Both first-year students and a group of engineering PhD students were used for the control sample.

5.1 Validation criteria

The objectives of the tests were to:

- a. estimate the *number of solutions* suggested for each problem
- b. define *breadth*, i.e. the number of solutions attributable to different physical effects.
- c. Compare results with those of a international test promoted by Iouri Belski using Matchemib [19].

5.2 Case studies

In order to test the efficacy of the method eight problems were considered: crankshaft breakage, killing lice in the scalp, removing ice from the wings of airplanes, cleaning the windows of skyscrapers, order box matches, rotate a solar panel to ensure its efficiency, stop leaks in oil pipelines. A final problem was about deposition of limestone residues in pipes, the same problem already proposed in a previous test on Matchemib. For each problem students had 16 minutes maximum for record all solutions on the

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software platform.

5.3 Main results

A first control group consisting of first-year students and a second control group consisting of PhD students was set up to evaluate the test. In addition, we had available the results of the International Matchemib Test Control Group [19]. The test showed that the mean of the solutions of the control sample was rather low, compared to the international sample. This can be explained by the fact that the current evaluation of the solutions was stricter, the solutions that resembled each other were all eliminated.

In contrast, there were no substantial differences between the control group consisting of first-year and doctoral students.

As shown in table 1, the results obtained by applying the proposed method to firstyear students are slightly lower than the results conducted with the international Matchemib test, while when it is applied by students skilled in TRIZ, it gives the best results, higher even than those of the international test (quite 7 solutions each vs 6,4 of international test students).

If we compare results with and without method, the first-year students improve the average from 2.5 to 6 (+255%), while students of international test made a growth of rate about 144%. Unfortunately, it was not possible to calculate the growth of rate for TRIZ students due to the lack of the corresponding control group.

For breadth the results are similar, but with some differences: the percentage growth for first year students using the method compared to their control group is +152%, very similar to what happened in the international Matchemib group, with +167%.On an absolute level, the average breadth for the first-year group is about 2.8 different physical effects, while 3.05 for the TRIZ group, and 4.7 for Matchemib (which is a method designed precisely to expand the breadth).

		Control Group			Results	
	1 year-	Phd-	Intern.	year-	TRIZ	Intern.
	Eng	Eng	Test	Eng	group	Test
n° solutions	2,3	2.9	4.4		6,95	6,4
rate of growth				$+255%$		$+144%$
breadth	1,85	l.9	2,8	2,8	3,05	
rate of growth				$+152%$		$+167%$

Table 1. Test results.

6 Conclusion and future developments

The method proposed in this paper is not an alternative to the traditional TRIZ approach, but it wants to be a contribute to systematize the research of the variants in the

early phases of the process. It does not help in the reformulation of complex problems, for example to better frame the problem and to reformulate it in simpler form. In fact, to use this tool it is assumed to have already defined the specific problem on which to intervene. From here the system can give hints to enlarge the number of the practicable ways. Initial results from a test of nearly 200 engineering students have shown that the proposed method can help triple the number of solutions to simple problems, while also increasing the variety of solutions in terms of physical effects. It can also help students who are TRIZ experts to further diversify their skills.

The results obtained are due to an impressive software infrastructure able to eliminate certain technological barriers that affected syntactic parsers in the past: due to the cost-effective availability of computing resources it is now possible to process large volumes of data in relatively short periods of time.

This system processes a corpus of many millions of documents without any form of limitation and it is able to manage all functional verbs from the over 100,000 verbs in the English language. Processed data are then made real-time searchable by keyword and also by mean of relationships between them.

Further developments will involve the use of BERT models, more precisely Google's Bert-for-patents [20], a BERT model trained on more than 100 million patent documents, trained on all parts of a patent (abstract, claims, description).

Finally, the latest innovation lies in graphic activators. At the moment it has not been possible to create a set of verbs for each functional verb, but the extension work is in progress and already in this way an important number have been covered.

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