Automatic classification of patents oriented to TRIZ: a case study on large aperture optical elements

Zhengyin Hu, Shu Fang, Wen Yi, Xian Zhang, Tian Liang Chengdu Document and Information Center, Chinese Academy of Sciences

> Leiden, The Netherlands Sept .2, 2014



1. Introduction

Research & Applications of Intellectual Property in CAS

- Information Portal: IP database, IP analysis tools, IP training, IP assessment, IP trading & transforming, etc.
- Intelligence products: IP rights information journal, IP analysis reports, IP consulting reports, Patents Tech Mining, etc.
- Services: custom data, intelligence products, consulting, training services for researchers, IP managers, IP policymakers, etc.
- Groups: IP management department of CAS, *IP Services group of CAS*, IP assistants in research institutes of CAS.



Classification Schema based on Patent Code



 International Patent Classification (IPC): 8 Sections, ~69,000 classes

US Patent Codes: 3 Groups, 462 Categories, ~153,000 classes

EPO Cooperative Patent Classification: extension of the IPC, adding 18,400 refined subclasses.

- A Human necessities
- B Performing operations, transporting
- C Chemistry, metallurgy
- D Textiles, paper
- E Fixed constructions
- F Mechanical engineering, lighting, heating, weapons, blasting
- G Physics
- H Electricity

Classifications Schema based on Contradictions & Principles



TRIZ: Russian acronym for Inventive Problem Solving Theory

Contradictions (Problems): basic and common problems in one area. 1201 standard engineering problems were summarized.

Principles (Solutions): basic and common solutions used for these problems. 40 Inventive Principles were summarized.

1. \$	Segmentation	
2. 1	Extraction, Separation, Removal, Segregation	
3. I	Local Quality	
4. /	Asymmetry	
5. (Combining, Integration, Merging	
6. I	Universality, Multi-functionality	
7. 1	Nesting	
8. (Counterweight, Levitation	
9. 1	Preliminary anti-action, Prior counteraction	
10	0. Prior action	

Advantage & Disadvantage of two classification schemas

Schema based on Patent Code :

Advantage: mature; focused on technology field Disadvantage: stable and kept invariant for a long time; too general to represent specific tech

Schema based on Contradictions & Principles :

Advantage: mature; focused on similar problems & solutions Disadvantage: stable and kept invariant for a long time; focused on machinery patents **Personalized Classifications Schema oriented to TRIZ**



Dynamic Schema: from specific patents set, more accurate with more details

Oriented to Problems & Solutions (P&S): help find patents with similar problems or solutions

 Rich Semantic Knowledge Representation (SKR): support deep tech mining on patents

2. Methodology

Construct Classification Schema

- Micro-Level(SAO)
- Meso-Level(P&S)

Macro-Level(Tech)

Preliminarily Classify Patents

Features Selection

Algorithms Selection

Compare Classifiers

Optimize Classifier

Smooth
Imbalanced Data

Reduce
Dimension of SAO

Construct Classification Schema



Micro-Level(SAO Semantic Units): extract Subject-Action-Object(SAO) triples from fields, such as Title, Abstract and clean SAO using *Term Clumping*.

Results: patents are represented as bag-of-SAO.

Tools: Relationship Extract Tool: Reverb,

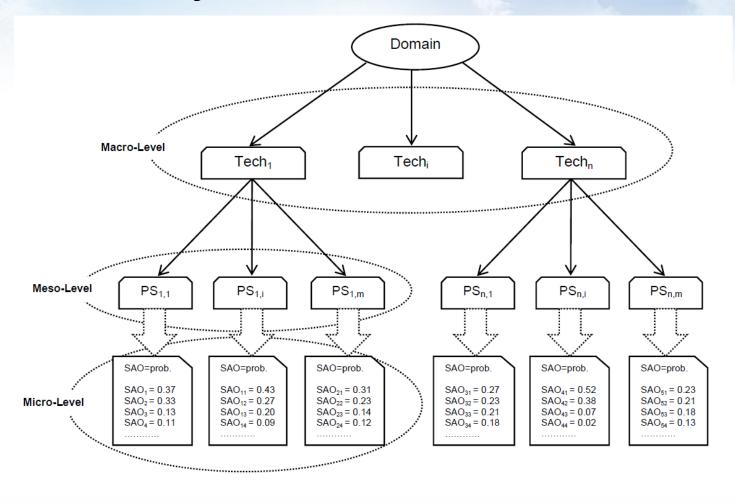
Text Analysis Software: Thomson Data Analyzer(VantagePoint)

 Meso-Level(P&S Topics): generate P&S topics based on bag-of-SAO of patents using LDA topic model.
Results: patent-P&S matrix, P&S-SAO matrix.
Tools: Machine Learning Toolkit : MALLET

 Macro-Level(Tech Topics): generate Tech topics based on patents-P&S matrix using LDA topic model.
Results: patent-Tech matrix, Tech-P&S matrix.

Construct Classification Schema

- $\overline{\mathbf{c}}$
- Experts: prune meaningless topics, summarize similar topics and attach labels to topics.



Preliminarily Classify Patents



Feature Selection: Information Gain (IG), Document Frequency (DF)

- Classification Algorithms : Maximum Entropy Classifier (MaxEnt), C4.5 Decision Tree Classifier (DT), Na ve Bayes(NB)
- Compare Classifiers: compare the accuracy based on the different combinations of features and algorithms and choose *best combination* to preliminarily classify patents on Test Sets.

Optimize Classifier



Smooth Imbalanced Data : optimize the training set by oversampling.

- Reduce Dimension of SAO: merge SAO by pattern rules to reduce dimensions of SAO features.
- Build a new classifier: apply the chosen combination of feature and algorithm on a new training set and SAO feature set.

3. Case Study

Construct Classification Schema



- Data set: choose Large Aperture Optical Elements (LAOE) patents as case study and get 1364 patents from Derwent Innovations Index(DII).
- Micro-Level(SAO): 2372 SAO were collected as the micro-level of the schema and patents were represented as bag-of-SAO.
- Meso-Level(P&S Topics): 200 P&S topics based on patents-SAO matrix were generated and experts chose 124 meaningful P&S topics as the meso-level of the schema.
- Macro-Level(Tech Topics): 20 Tech topics based on patents-P&S matrix were generated and experts summarized 4 Tech domain topics as the macro-level of the schema.

Construct Classification Schema



Part of the personalized LAOE patent classification schema

Class	Tech Domains	P&S Topics	SAO semantic units
No.			
C1	Measuring surface	P&S ₁₀ (<i>p</i> =0.557)	check large lens convex surface;
	shape	$P\&S_{11}(p=0.213)$	measure surface roughness;
		$P\&S_{14}(p=0.117)$	analyze object surface profile;
C 2	Surface measuring	$P\&S_1(p=0.628)$	method measure diffraction;
	method	P&S ₃₉ (p=0.124)	method measure optical curvature;
		$P\&S_{114}(p=0.017)$	method analyze interference-fringe;
C3	Surface measuring	$P\&S_{15}(p=0.415)$	device measure wave aberration;
	device	$P\&S_{79}(p=0.354)$	shear interferometer for flatness;
		$P\&S_{102}(p=0.203)$	device measure lens deflection;
C 4	Online monitoring	$P\&S_{27}(p=0.813)$	monitor surface quality;
		$P\&S_{42}(p=0.102)$	control optical surface quality;
		$P\&S_{78}(p=0.005)$	inspect surface shape;

Preliminarily Classify Patents



We choose 100 patents as training set. And experts manually classify these patents to {C1, C2, C3, C4} as the training set.

- Feature Selection: top 5,10 and 20 IG SAO; DF above the threshold 2,3 and 5 SAO;
- Algorithms Selection: Maximum Entropy Classifier (MaxEnt), C4.5 Decision Tree Classifier (DT), Na ïve Bayes(NB) in Mallet

Accuracy of Classifiers on Training Set

MaxEnt(%)	DT(%)	NB(%)
67.6%	74.6%	72.6%
73.5%	82.8%	80.5%
71.3%	77.2%	79.1%
57.2%	65.2%	71.2%
52.6%	68.9%	69.3%
59.3%	72.7%	74.8%
52.6%	68.9%	69.3%
	67.6% 73.5% 71.3% 57.2% 52.6% 59.3%	67.6% 74.6% 73.5% 82.8% 71.3% 77.2% 57.2% 65.2% 52.6% 68.9% 59.3% 72.7%

Average Classification Results on 3 Test Sets

Class No	Precision	Recall	F-measure
C1	0.764	0.72	0.741
C2	0.792	0.64	0.708
С3	0.832	0.78	0.805
C4	0.718	0.72	0.719
{C1,C2,C3,C4}	0.784	0.72	0.743

Average Classification Results on Test Sets after Optimization

Optimization Strategy: over-sampling to build a new training set and merging SAO to build a new classifier

Class No	Precision	Recall	<i>F</i> -measure
C1	0.884	0.82	0.851
C2	0.926	0.88	0.902
C3	0.782	0.78	0.781
C4	0.726	0.86	0.787
{C1,C2,C3,C4}	0.830	0.84	0.830

Result



- The SAO triples are more suitable as basic semantic units than keywords in patent tech mining oriented to TRIZ.
- Topic model can help mine P&S topics from SAO triples and Tech domains from P&S topics.
- The personalized classification schemes oriented to TRIZ can help deep patent tech mining.
- The dimension reduction of SAO based on pattern rules is important to the results of classification.

Discussion



- It is a challenge to automatically distinguish the Problems or Solutions from the topics generated on SAO triples.
- Less SAO is good for better feature selection, but is not good for topic model. There are two different SAO clumping standards for topic model and feature selection.
- The personalized classification schemes can be used as semantic index. How to apply it for other applications?

