國立雲林科技大學
101學年度博士班招生考試試題

系所別：資訊管理系
科　目：資訊管理文獻

Answer the following questions:

1. Please read the article. Write the abstract in English and no more than 300 words. In the abstract, it should include the followings:

a. Main issues (10%)
b. Research methods (5%)
c. Data collection procedure (5%)
d. Results (10%)
e. The findings (20%)

2. The two basic theories in this article are the cultural historical activity theory (CHAT), and the Knowledge Navigator Model (KNM). Which of these two theories is the most important? Why? The least important? Why? (15%)

3. Evaluate the advantage and disadvantage of the statistic analysis method in this article. (10%)

4. What is the management implementation that we discussed the research result and finding in this article. (10%)

5. What are the components of the tendency of all barriers to knowledge flow? Explain how the tendency is related to the other barriers dimension. (15%)

Information & Management 49 (2012) 10–23

Contents lists available at SciVerse ScienceDirect

Information & Management

journal homepage: www.elsevier.com/locate/im

Exploring barriers to knowledge flow at different knowledge management maturity stages

1. Introduction

In implementing a KM system in an organization, it is important to understand what and how different barriers to knowledge flow affect its progress, as well as knowing how both your firm and your opponents can win in the competitive environment. Hence, it is important for organizations to assess difficulties they may meet while implementing KM initiatives.

During the last few decades, there have been several KM initiatives that have been widely studied. An industry survey of 811 large enterprises in North America and Europe conducted by Desouza [10] in 1999 revealed that 90% of them recognized the importance of KM, and most of them had KM activities underway. In addition, a study by AMR Research [3] estimated that companies in the United States would spend close to $85 billion on KM in 2008, an increase of nearly 16% from 2007.

To business entities, KM is an essential managerial activity if they are to sustain their competitive advantages in today's information economy. There has been a corresponding wave of interest both from researchers and practitioners recently. Knowledge has been recognized as a critical resource [28], as it provides the foundation for competitive advantages. Knowledge allows organizations to predict the nature and commercial potential of changes in the environment, as well as the appropriateness of their strategic decisions. The ability of firms to capture, organize, and disseminate knowledge allows them to improve the quality of decision making, process efficiency, customer satisfaction, and cost control. As knowledge has been widely recognized as a valuable resource in helping organizations to sustain competitive advantages, firms are increasingly investing in KM initiatives to promote the sharing, application, and creation of knowledge to develop more competitive situations and attain business goals [22,16].

Still, there are a number of challenges that arise during the KM developing progress. For example, knowledge is a complex and multi-faceted concept in and is embedded in many entities and/or activities in an organization, including the organization's culture, policies, documents, and the employees [15]. The problems of KM implementations vary according to the context and KM maturity level. While research into and practices of KM have recently grown rapidly, the KM field has been criticized as being confusing due to lack clarity with respect to its definitions and framework. To overcome these problems, Knowledge Management Maturity (KMM) [21] provides a way to evaluate each level of KM progress; in this context maturity is the extent to which a specific process is explicitly defined, managed, measured, controlled, and effective. Although many studies have considered the potential benefits of

* Corresponding author. Tel.: +86 2162829243.
E-mail address: yendc@muohio.edu (D.C. Yen).

0378-7206/$ – see front matter
doi:10.1016/j.im.2011.11.001

KM, very little attention has been paid to surveying professionals about their way of developing KM and assessing the issues related to its maturity and clarity [4].

In our study, we first proposed that barriers to knowledge flow are likely to be different at different KM maturity levels. We therefore explored what and how they are changed when KMM levels change, and examined the influence and impact of change at each level. To achieve this, a revised CHAT model [20] was used to classify the barriers comprehensively, and a Knowledge Navigator Model (KNM) [14], was adopted to evaluate the KM maturity level. In order to explore the dynamics of the barriers to knowledge flow in different KMM levels, a longitudinal observation survey, questionnaires, in-depth face-to-face interviews, and quantitative analysis were conducted with the cooperation of KM experts in seven firms.

2. Theoretical background

2.1. Knowledge flow

Although knowledge flow is invisible it works with any cooperative team, whether used it intentionally or not. It has been defined as a process of knowledge passing between people or knowledge processing mechanisms; Zhuge [30] stated that it was "the passing of knowledge between nodes according to certain rules and principles." Here a *knowledge node* is a team member or role, or a knowledge portal or process. A node can generate, learn process, understand, synthesize, and deliver knowledge. Organizational knowledge flows can be greatly facilitated if knowledge is codified; i.e. packaged into formats that allow its transmission to other subunits.

In our research, knowledge flow was viewed as experience and knowledge that was independently created and exchanged by any organization interacting with another organization in order to diffuse, accumulate, or share knowledge. In addition, knowledge flow was seen as a process whereby knowledge was passed between people or mechanisms. In order to describe and classify the barriers to knowledge flow, we adopted a revised CHAT model, see Fig. 1.

2.2. Determinants of and barriers to knowledge flow

Several factors affect the performance of knowledge flows, such as

- the value of the source unit's knowledge stock,
- the motivational disposition of the source unit,
- the existence and richness of transmission channels,
- the motivational disposition of the target unit, and
- the absorptive capacity of the target unit.

These factors can be classified into dimensions of knowledge source, receiver, and processing mechanism.

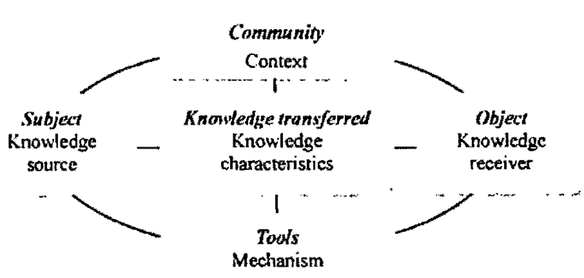


Fig. 1. A revised CHAT model applied to knowledge flow [12].

Also, knowledge flow is probably influenced by knowledge transfer, source, receiver, and context. Knowledge flow has three crucial attributes: direction, content, and carrier; these determine the sender and the receiver, the sharable knowledge content, and the media. The related entities include factors of knowledge flow that can become barriers if they are not given the appropriate attention or properly applied. The theory of reasoned action employed extrinsic motivators, social psychological forces, and organizational climate factors to explain the individual's knowledge sharing intentions [7]. In our study, we adopted the revised CHAT model that has been found to be a useful approach to classifying the determinants of knowledge flow in the healthcare industry, and added other factors derived from various other studies. For commercial business operations, we classified the relevant determinants and barriers to knowledge flow onto five dimensions: knowledge characteristics, knowledge source, knowledge receiver, contextual factors, and mechanisms, see Table 1.

2.3. Knowledge management maturity model

Organizations implement KM practices and technologies based on the promise of increasing their effectiveness, efficiency, and competitiveness. Maturity is the extent to which a specific process is defined, managed, measured, controlled, and effective. In practice, it can be considered as a way for organizations to achieve their KM maturity level and to adopt an adequate strategy. Maturity models that depict the development of an entity are a natural application of the life-cycle process and they can be used to advance maturity by identifying and implementing the steps required to move to a higher level. In this context, the KMM was conceived to aid KM implementation.

There are various well-known maturity models for different purposes, such as the Capability Maturity Model (CMM) and the Capability Maturity Model Integration (CMMI) for software development published by the Software Engineering Institute with five levels of maturity, from initial, repeated, defined, and managed, to optimizing [25]. Some of the KM maturity models used in practice are KPMG's Knowledge Management Framework Assessment Exercise—Knowledge Journey; Tiwana's 10-Step KM Roadmap; Kochikar's KMM Model, which is used in Infosys' KM program; Siemens's Knowledge Management Maturity Model (KMMM); Wisdom Source's Knowledge Management Maturity Model (K3M); APQC's Knowledge Management Maturity Model APQC's Stages of Implementation; and a General KM Maturity Model (G-KMMM) that encompasses the initial, aware, defined, managed, and optimizing stages; they are differentiated in terms of their characteristics related to the people, process, and technology aspects of KM [22].

Maturity in KM is seen as a series of dynamic stages that can be completed through consistent and concentrated efforts. To sustain continuous growth, firms need to advance to the *next* level of maturity. KPMG presented four KM key areas in its model: people, process, content, and technology, with each having activities to be completed. Firms can be assessed according to the way that they implement these activities by applying the five-level Knowledge Journey, which includes: Level I: Knowledge Chaotic; Level II: Knowledge Aware; Level III: Knowledge Focused; Level IV: Knowledge Managed, and Level V: Knowledge Centric. Tiwana advanced the 10-step KM Roadmap by classifying it into four phases: (1) infrastructural evaluation; (2) KM system analysis, design, and development; (3) system deployment; and (4) performance evaluation. The 10-step KM roadmap connects business strategy and KM, and assists in designing, developing, and deploying a KM system, which can then be used to deliver actual business results.

Table 1
Relevant determinants of knowledge flow found in the literature.

Dimension	Barriers to knowledge flow and [source]
Knowledge characteristics	Ambiguity [20]
	Non-validated knowledge [20]
Knowledge source	Unwilling to devote time and resources to sharing knowledge [20]
	Fears about job security [24,12]
	Low awareness and realization of knowledge sharing [20,24]
	Fear loss of ownership [26,23]
	Not adequately rewarded [20,26]
	Sense of self-worth [20]
	Poor communication skills [24]
	Lack of trust in people [12,5]
Knowledge receiver	NIH syndrome [20]
	Lack of absorptive capability [20,9]
	Lack of retentive capacity
	Lack of trust in knowledge [24,12]
	Untrustworthiness [7,5]
	Lack of contact time and interaction [24]
	Differences in experience level (i.e. individual perceptions of approachability) [24]
	Difficult relationships [7]
	Lack of awareness
Contextual factors	Culture and cultural characteristics [20,5]
	Organizational structure
	Poor physical work environment
	Lack of spaces to share
	Excessive size of business units
	Time and resource constraints
	Lack of organizational incentives [5,13]
	Lack of leadership [20,5]
	Lack of complete or standard regulations [14]
	Lack of coordination between units [24]
	Geographical dispersion
	Context differentiation
	Competitiveness
	Different languages [5]
	Overly technical terminology [18]
Mechanisms	Lack of tangible mechanisms such as telephones, conference rooms or computer networks [12]
	Failure to develop a transactive memory system [5]
	Lack of intangible mechanisms such as unscheduled meetings, informal seminars, or coffee break conversations [12]
	Lack of integration of IT systems and processes [8]
	Lack of compatibility among diverse IT systems
	Unrealistic expectations of employees and mismatches with individual needs [27]
	Employees lack familiarity and experience with new IT systems
	Lack of training regarding new IT systems
	Lack of communication with employees about the advantages of the new system [1,2]

Source: This research.

A comprehensive KM maturity model is necessary to navigate and assess the development of KM. However, the current KM maturity models lack an evaluative framework with detailed items and procedures, and this might result in low procedure comprehension by users and researchers. The Knowledge Navigator Model (KNM) proposed by Hsieh et al. can thus be used to evaluate an enterprise's KMM with regard to its culture, knowledge process, and technology. On the basis of an assessment of KNM, a firm is placed in one of five stages. Stage I: Knowledge Chaotic; Stage II: Knowledge Conscientious; Stage III: KM; Stage IV: KM Advanced, and Stage V: KM Integration. Details of some of the well-known KMM models are shown in Table 2.

2.4. *Knowledge Navigator Model, KNM*

The basic concept of KNM was developed along with the Capability Maturity Model for Software (CMMI) and the Road Map to Knowledge Management Results Stages of Implementation.

Table 2
Some well-known KMM models.

KMM model	KMM Level I	KMM Level II	KMM Level III	KMM Level IV	KMM Level V
KPMG Knowledge Journey	Knowledge chaotic	Knowledge aware	Knowledge focus	Knowledge managed	Knowledge centric
Tiwana's 10-step KM Roadmap	Infrastructural evaluation	Analysis, design, and development	System deployment	Performance evaluation	–
Kochikar KMM model in Infosys	Default	Reactive	Aware	Convinced	Sharing
Siemens KMMM	Initial	Repeated	Defined	Managed	Optimizing
APQC KMMM	Initiate	Develop	Standardize	Optimize	Innovate
G-KMMM	Initial	Aware	Defined	Managed	Optimizing
Hsieh KNM	Knowledge chaotic stage	Knowledge conscientious stage	KM stage	KM advanced stage	KM integration stage

Source: This research.

	Culture	*KM Process*	*IT*
	Culture and People– their "mindset" – it relates to attributes assessing people and culture.	Process, policy and strategy- this facilitates and guides the efforts of people to capture and use organizational knowledge to achieve business	Technology and infrastructure- the enablers that help people obtain the benefits from the KM initiative.
Level V KM integration	The organization uses regulations and culture to sustain KM development.	The organization integrates knowledge and the network environment.	The KM technical environment supports the integration of knowledge.
Level IV KM advanced	The organization confirms KM executing through regulations and culture.	The organization can qualify and quantify KM performance.	The organization has a technical environment to support KM.
Level III KM	The organization promotes KM through regulations and culture.	The organization defines, shares, captures, stores, and uses knowledge.	The organization has a technical environment to support KM.
Level II Knowledge conscientious	The employees are aware of the importance of KM.	The employees define, share, capture, store, and use knowledge.	The organization nurtures a technical environment for KM.
Level I Knowledge chaotic	The employees recognize the concept of KM.	The employees define, share, capture, store, and use knowledge in their own way.	The organization has a computer environment, and members have basic

Fig. 2. Three target management objectives in terms of KNM [24].

The KNM basically consists of two major frameworks: the *evaluation framework* collected users' preferences for assessment, while the *calculation* process counted the evaluation scores to determine the KM maturity stage. This method was adopted to assess the knowledge maturity level of enterprises in Taiwan by CPC (the China Productivity Center), which was the first and is now the largest management consulting agency in Taiwan. In the last few decades, many firms (especially public companies) in Taiwan have been evaluated using KNM to categorize their KM development and identify their KMM stage. In addition, our sample companies' KM implementation, all operate under CPC's guidance. The content of three target management objectives and the characteristics of the KNM's five levels are shown in Fig. 2.

3. Research methodology

We approached our research mainly from a knowledge flow and KMM perspective, and the process primarily involved a longitudinal survey, using questionnaires containing items related to barriers to knowledge flow, KMM model, and the background of the sample companies. In order to probe more deeply into barriers differences, KMM level, and the sample firms' background variables, face-to-face interviews using content analysis procedures were conducted with senior experts from the companies; our content analysis involved both descriptive and thematic parts. Finally, in order to confirm and strengthen our research findings, the Delphi method was used to obtain consensus with regard to expert opinions through a series of questionnaires that collected and aggregated experts' informed judgments on specific questions and issues. The Delphi study used people who had been actively involved in a number of KM implementations as either a manager or a principle investigator.

3.1. Research process

The process of data gathering resembled using a filter to continuously extract data. Some temporary conclusions were obtained in the initial analysis and the semi-structured questionnaire was continuously modified based on the conclusions of each phase; i.e. the data was re-checked in the next phase of interviews and then re-confirmed by Delphi analysis. Semi-structured questionnaires were designed to conduct in-depth interviews to acquire open-ended data, as this allowed the participants to digress and helped researchers to obtain broader and deeper information about knowledge flow at different KMM stages.

Barriers to knowledge flow were collected from earlier studies and then categorized into the following five dimensions of the revised CHAT model: knowledge characteristics, knowledge source, knowledge receiver, contextual dimension, and mechanisms. In-depth interviews with experts at the firms were

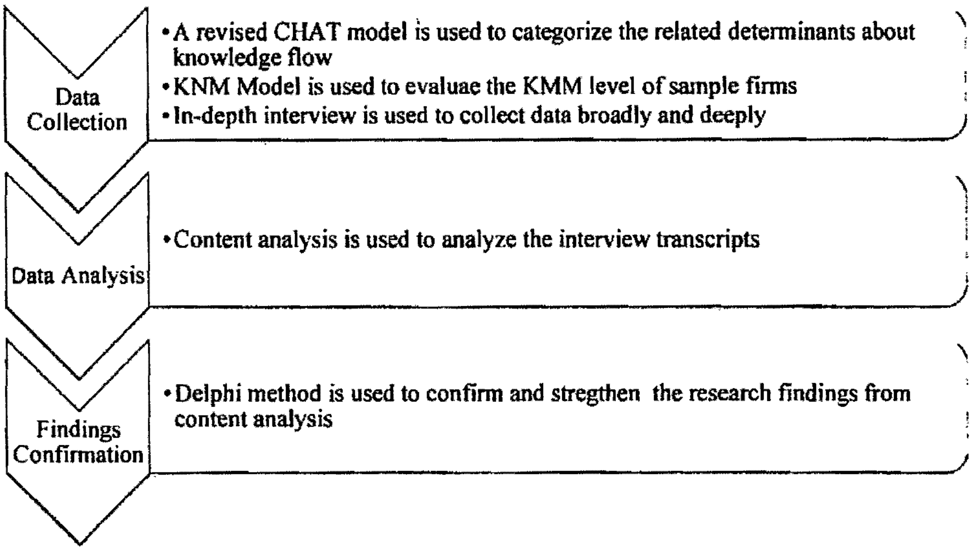


Fig. 3. The research process.

conducted to find any missing barriers. The firms were then evaluated using a KNM assessment to identify their stage: Knowledge Chaotic, Knowledge Conscientious, KM, KM Advanced, or KM Integration. Firms at every KNM stage were invited to participate in our research.

The in-depth interviews were used to collect general data, and content analysis was then used to analyze it, with some phenomena using different perspectives or KNM stages. The Delphi method was then used to obtain consensus on the opinions of the experts through a series of questionnaires that collected and aggregated responses to specific questions. The research process and tasks in each phase is shown in Fig. 3.

3.2. Instruments

The survey instruments used in our study were designed to measure the barriers to knowledge flow and the level of KM maturity with respect to the prior research process as shown in Fig. 3. The pre-test and post-test were conducted using questionnaires from previous studies to evaluate the KM level of each selected firm both before and after face-to-face interviews. A Delphi survey interview guide was used to test the findings of content analysis empirically, and to explore the relationships between barriers to knowledge flow and KMM level in more detail. All of the instruments were provided in both English and Chinese so that participants fluent in either language could understand the questions. These instruments were tested in several stages and were found satisfactory, reliable, and valid. All of the interviews were audio-taped and transcribed verbatim. In addition to the interview content, observations and informal conversations also played important roles in the process of data collection. If the information was ambiguous or insufficient, we contacted the interviewee again to recheck the data. The questionnaires and interviews were guided by the interview instrument, as shown in Appendix A.

3.3. Data collection

A total of 37 barriers to knowledge flow were discovered from reviewing the previously published literature; they were classified into the five dimensions of the revised CHAT model. In-depth interviews were then used to collect data from the selected companies. A pre-test was used to evaluate the KM maturity level of the sample firm before the interview. This helped the interviewers to understand the effects of the barriers to knowledge flow in each KM maturity level. In addition, some interesting and significant concerns from experts were revealed during this phase. Also, the interviewees were able to check the significant barriers to knowledge flow in their own companies before attending their interview.

A semi-structured questionnaire was designed for the in-depth interviews with managers from seven companies who had implemented knowledge management in Taiwan. This semi-structured questionnaire allowed researchers to capture detailed data about the issues and allowed flexibility in exploring additional issues raised by the participants.

Data collection occurred from February 2009 to July 2010. The data sources included nonparticipant observation, a pilot version questionnaire, face-to-face interviews, a post-test, stimulus-recall reports, and finally, a Delphi analysis.

3.4. Sample characteristics

As a part of the longitudinal survey, the subjects and participants were selected based on their having no confidentiality concerns and being available for longitudinal observation. Seven companies were selected according to their KNM level in CPC's list, with one company from KNM levels I, II, and V, and two companies from KNM levels II and III. There are few companies at KNM level V, and therefore we invited IBM, to participate in our research. The sample companies and the major participants who were asked to participate in the survey and interviews are shown in Table 3. Each interviewee was asked to evaluate their company's KNM stage before and after the interview. The participants in this study were closely engaged in KM and had a rich variety of related practical experiences.

4. Analysis and results

4.1. Analysis process

The first stage in the qualitative analysis was to examine the transcripts of the face-face interviews in order to determine their structure and the direction of the interaction. All the information

Table 3
The profile of subjects and participants.

Subject					Participant		
Sample	KNM stage	Industry	Established (years)	Employees	Position	Department	Tenure
A	I	Electronics	23	10,333	Senior Supervisor	President's Staff Office	4
B	II	Chemicals	54	1300	Director	Information Technology Division	15
C	III	Electronics	25	19,000	General Manager	Research and Development Department	5
D	III	Consulting services	55	433	Associate Vice-President	Planning and Training Division	11
E	IV	Automotive	39	1900	Deputy General Manager	Knowledge Department Section Corporate Planning Division	11
F	IV	Steel	37	9400	Administrator	Manpower Development Section Human Resource Department	33
G	V	Consulting services	99	390,000	Executive	Central and Southern Taiwan	19

from the surveys and interviews was coded for statistical and content analyses. Descriptive statistical analysis was employed to the structured questions, while thematic analysis was used to analyze the interview transcripts to obtain open-ended data. Thus the interview data was narrowed down to information-rich quotations that were ultimately placed into thematic categories.

The content of all the interviews had been transcribed from audio-tape records using a standard word processing program. All of the transcripts were reviewed by experts and the statements pertaining to key themes, that had been pre-determined from prior literature, were highlighted. In order to ensure the quality of the content analysis, three experienced researchers were invited to participate in our study. All disputes about statement selection or major themes were discussed until a consensus was reached, if possible.

To analyze the findings and better understand the research implications, all the barriers were mapped onto the revised CHAT model and then simplified into four dimensions as shown in Table 4.

4.2. Reliability and validation

In our study, the research design combined several methods with the criteria of credibility, transferability, dependability, and conformability to enhance the reliability and validity of the results, as well as triangulation by the use of multiple, different methods, investigators, sources, and theories to obtain corroborating evidence.

The content validity of the survey instruments was established by adopting instruments that had been used and validated by other researchers. The validation of reliability and inter-coder agreement was measured to ensure the trustworthiness and authenticity of our analysis. After several rounds and discussion by experienced researchers, 276 themes were found from the content analysis, and 237 of them were selected by all three coders. Thus the degree of inter-coder agreement was 93.2%, and their reliability was 96.7%. The classification among the coders presented a consistent viewpoint with regard to the thematic analysis. Moreover, company G at Stage V in the KNM was too mature to exhibit many barriers to knowledge flow. The details of the reliability and inter-coder agreement are shown in Table 5.

4.3. Results of content analysis

After analyzing all of the responses from the interviews, data gathered from the participants was used to summarize major findings from interviews and content analysis, as shown in Table 6.

In addition, there were some barriers revealed through analysis of the face-to-face interviews; these rarely appeared in previous studies but were significantly related to the performance of the KM implementations, and include lack of authority (D27), technophobia (R12), lack of trust in system security (S32), and systematic knowledge documentation (M24).

4.4. Results of the Delphi survey

A two-round Delphi survey was used to strengthen the findings: the first was held in June 2010, after the data analysis and the second was conducted one month later. Twelve experts were selected from the middle management level of public companies in Taiwan; all of them were familiar with KM implementations, the ecosystem of knowledge flows in business organizations, and KM maturity models. In order to avoid any subjective bias, the 12 panelists were selected from different companies.

The panelists were asked for their comments on: (1) the importance of barriers to knowledge flow; (2) the appropriateness and importance of each barrier to knowledge flow; (3) the potential relative importance of barriers in each KMM stage; and (4) the tendency of the barriers to knowledge flow along with KM maturity level changing. In addition, they were asked to describe the reason that they agreed or disagreed with questions shown in Appendix A. A five-point Likert scale was used for responses. All respondents replied the first round and an agreement level of greater than 85% was found. The results of the Delphi study after two rounds were:

(1) The significant dimensions of barriers to knowledge flow at each KMM level.

In KMM level I, contextual dimension was regarded as the most important domain by most of the experts. Most companies were in this stage and had just realized the importance of KM, but the size of these firms was relatively small and their resources for KM implementation were limited. Their major managerial activities were general business operations and routines. For these companies, the first KM task was to determine how to identify and extract knowledge from documents and processes. In addition, the type of knowledge at this stage was usually unstructured and needed to be translated into structured and explicit formats, such as standard operating procedures (SOP) or official documents.

In KMM levels II and III, mechanism was the main domain, since companies at this stage were able to engage in KM implementation and were ready to construct suitable mechanisms, such as a KMS, to undertake KM activities more efficiently. Its principle functions were to facilitate: conversion of data and text into knowledge; conversion of individual and group knowledge into accessible knowledge; linking of people and knowledge to others and structure the knowledge; communication of information between groups; and creation of new knowledge that would be useful to the organization [17].

In KMM Level IV, the role of knowledge characteristics and its complex nature were more important, especially in how to transfer tacit to explicit knowledge. There are many examples of companies that have not accomplished their objectives in

Table 4
Codes of themes.

Dimension	Sub-dimension	Barriers to knowledge flow	Code
Knowledge characteristics		1. Ambiguity	C01
		2. Non-validated knowledge	C02
Knowledge source	1. Lack of motivation	1. Lack of time	S11
		2. Fear of reducing job security	S12
		3. Low awareness and realization of knowledge sharing	S13
		4. Fear of losing intellectual property rights	S14
		5. Not adequately rewarded	S15
		6. Threat to sense of self-worth	S16
	2. Lack of ability	1. Poor community skills	S21
	3. Lack of trust	1. Lack of trust in people	S31
		2. Lack of trust in system (security)[a]	S32
Knowledge receiver	1. Lack of motivation	1. NIH syndrome	R11
		2. Technophobia[a]	R12
	2. Lack of ability	1. Lack of absorptive capability	R21
		2. Lack of retentive capacity	R22
	3. Lack of trust	1. Lack of trust in knowledge	R31
		2. Lack of trust in system (security)[a]	R32
Contextual factor	Relationships between knowledge sources and knowledge receivers	1. Untrustworthiness	D11
		2. Lack of contact time and interaction	D12
		3. Differences in experience level	D13
		4. Difficult relationships	D14
		5. Lack of awareness	D15
	Organizational context	1. Culture and cultural characteristics	D21
		2. Organizational structure Poor physical work environment Lack of spaces to share Excessive size of business units	D22
		3. Time and resource constraints	D23
		4. Lack of organizational incentives	D24
		5. Lack of leadership	D25
		6. Lack of complete or standard regulations	D26
		7. Lack of authority[a]	D27
	Other contextual factors	1. Lack of coordination between units Geographical dispersion Context differences Competitiveness	D31
		2. Different languages	D32
		3. Overly technical terminology	D33
Mechanisms	Lack of mechanism	1. Lack of tangible mechanisms	M11
		2. Failure to develop a transactive memory system	M12
		3. Lack of intangible mechanisms: unscheduled meetings, informal seminars, or conversations	M13
	Lack of integration	1. Lack of integration of IT systems and processes	M21
		2. Lack of compatibility between diverse IT systems	M22
		3. Unrealistic expectations of employees and mismatch with individual needs	M23
		4. Lack of coordination in knowledge documents	M24
	Lack of training	1. Employees are unfamiliar with and lack experience with new IT systems	M31
		2. Lack of training of new IT systems	M32
		3. Lack of communication with employees about the advantages of the new system	M33

[a] Additional determinants of knowledge flow from face-to-face interviews.

knowledge-sharing due to the large diversity of potential sharing barriers and the types of knowledge [24]. However most KM implementations have successful and their KM goals are refining knowledge and creating niches storing their intelligence assets.

In KMM Level V, people (both knowledge providers and receivers) and contextual domains are simultaneously important, since the companies at this stage are mature enough to extract and store rich tacit and explicit knowledge within their knowledge management system. Previous debates about knowledge sharing and management disciplines usually argue that it is mostly about people and adaptations to the social dynamics of the workplace rather than technology. The main task for companies at this stage was found to be strengthening positive interactions between providers and resources by developing a suitable context.

(2) The significant barriers to knowledge flow in each KMM level.

Participants responded to this section by using a Likert scale from 1 to 5, indicating the degree to which they agreed or disagreed with the questionnaire statements. The means and standard deviations of analyses at different KM maturity levels were computed from the participants' responses, and these are presented and coded in Table 5. Most of the participants endorsed the concept that a better understanding of barriers to knowledge flow at each KMM level played a positive role in their current KM implementations and experience. Among the 42 items, all received relatively significant means ($M > 3.0$), suggesting that they were common beliefs held by the

Table 5
The reliability and inter-coder agreement of the thematic analysis.

KNM stage	I	II	III		IV		V	Total
Firm code	A	B	C	D	E	F	G	
Selected themes	38	37	67	57	33	34	10	276
Agreed themes	34	33	61	48	28	28	9	237
Inter-coder agreement	0.944	0.943	0.953	0.914	0.918	0.903	0.972	0.932
Reliability	0.971	0.971	0.976	0.955	0.957	0.949	0.953	0.965

Table 6
Main findings and significant barriers in each KMM stage.

KMM stage	Main findings	Dimension	Significant barriers
I	Organizations and their members have low awareness of the importance of KM, and a lack of leadership Lack of leadership (D25) is the critical barrier to knowledge flow in this stage	People (provider and receiver) contextual mechanisms	S13, S31, D21, D25*, D26 M23, M31
II	Managers sense the importance of KM to their organization, but their members and KM related mechanism are not ready for knowledge sharing	People (provider and receiver)	
	Lack of time (S11), lack of leadership (D25), and the unrealistic expectations of employees and mismatch with individual needs (M23) are the most critical barriers in this stage; showing a gap between top managers and employees	Contextual	S11*, S32, D21, D24, D25*, D26, D33, M23*
III	The unrealistic expectations of employees and mismatch with individual needs (M23) are the critical barriers in this stage. However, interactions among members in organizations have frequently occurred when an appropriate reward system is established	People (provider and receiver) contextual mechanisms	S11, S14, S15 D12, D13, D22, D25, D31, D33 M12, M21, M23*
IV	Valuable knowledge is hard to identify and transfer, especially from explicit to tacit knowledge, and one of the critical barriers is ambiguity in the knowledge (C01) A large volume of information and knowledge are common phenomena in this stage, and members are seriously concerned about the compatibility between IT systems (M22) Valuable knowledge identification, knowledge repository, knowledge presentation, and mechanism integration are the main concerns in this KMM stage	Knowledge Characteristics mechanisms (integration)	C01*, S12, S22, D25, D27*, D31 M22*, M23, M24, M31
V	The barriers to knowledge flow are less significant. The real value of knowledge is not in the KM system, but in how the knowledge flows or is shared to create and sustain long-term business development. The barriers to knowledge are different from those in previous stages	Contextual and mechanisms (integration)	D27*, M21

* Significant ($\geq$10%).

participants; eight items (C01, C02, S11, S16, D25, D27, M22, and M23) had higher means ($M > 3.5$), and thus were categorized as the principle ones. These barriers to knowledge flow at each KMM stage were confirmed by experts. They were all strongly related to knowledge flow either within an organization or across the organization, and the relationships among them played a critical role in smooth knowledge sharing and its flow within the organization [16,11].

(3) The tendency of barriers to knowledge flow.

Because there are progressive changes in barriers to KM development over time, the barriers to knowledge flow can be classified into five trends: *existence* (the barriers never change as KM develops), *decline* (barriers lessen), *increase* (barriers grow), and *random* (barriers are dynamic). Table 7 shows the direction of the various barriers to knowledge flow.

Table 7
The tendency of barriers to knowledge flow along with KM maturity level changing.

Tendency	Barriers to knowledge flow
Existence	Lack of time (S11) Low awareness and realization of knowledge sharing (S13) Fear of losing the ownership of intellectual property (S14) Lack of leadership (D25) Unrealistic expectations of employees and mismatch with needs (M23)
Decline	Not adequately rewarded (S15) Lack of contact time and interaction (D12) Lack of organizational incentives (D24) Lack of complete or standard regulations (D26) Overly technical terminology (D33) Failure to develop a transitive memory system (M21) Employees lack familiarity and experience with new IS (M31).
Increase	Authority (D27) Lack of coordination between units (D31) Lack of integration of IT systems and processes (M21) Lack of compatibility between diverse IS (M22) Lack of systematic knowledge documentation (M24)
Random	Technophobia (R12) Lack of trust in system (S32), Untrustworthiness (D11) Culture and cultural characteristics (D21)

The research findings were filtered using analysis methods for each task; the results are summarized in Table 8.

5. Discussion of findings

The related issues and implications are discussed from three perspectives:

Table 8
Summary of research results and findings.

Task	Analysis result	Participant
Literature review pre-test	37 determinants of barriers to knowledge flow were classified into five dimensions based on the revised CHAT model Seven sample firms were selected and categorized into five KMM levels from responses to the pre-test questionnaire	Sample firms selected from CPC list
Face-to-face interviews	In-depth face-to-face interviews An additional four determinants (R12, S32, R27 and M24) were found from face-to-face interviews	The participants of sample firms in our study
Content analysis	226 themes referring to the initial 37 determinants were selected from the transcripts A total of 25 determinants were found, calculated, and analyzed based on their frequency in the transcripts	The researchers in our study
Data validation	226 themes were selected; 232 were agreed to by all the researchers	The researchers in our study
Post-test	Evaluate the KM maturity level of sample firms to re-check the change of level during the research period Research findings were confirmed by the experts of the sample firms Four tendencies of barriers to knowledge flow along with KM maturity level changing were confirmed again by experts.	The researchers in our study The participants of sample firms in our study
Delphi study	The importance of barriers to knowledge flow in different knowledge management maturity levels was investigated The significant barriers to knowledge flow in each KMM level were identified The appropriateness of barriers to knowledge flow were identified	12 experts who were familiar with KM implementations, the ecosystem of knowledge flows in business organizations and KM maturity models

Source: This research.

(1) The barriers to knowledge flow are different at different KMM levels and they change in association with KM development.

The benefits of using maturity models to explore the barriers to knowledge flow are that they provide the following a better understanding of the current status of KM activities when organizations are implementing KM; a road map for navigating the barriers in different stages; and a guide to help KM activities move on to the next stage [19].

In the early stages, people and contextual domains play a critical role in KM implementations, and powerful leadership is necessary. In addition to people and contextual domains, mechanisms become important in KM development, especially in KMM stages II and III. Also, the barriers to knowledge characteristics become more important in the later stages, and the barriers are mainly progressive integration issues.

(2) The characteristics and barriers to knowledge flow change as the KMM develops.

We classified the 21 barriers into four types and these revealed the critical barriers at various stages of the KMM. Generally, most barriers at a stage were dependent on the behavior of the members of the organization (including leaders, knowledge providers, and receivers). Support from top management and experienced leaders are very important. In addition, the behavior and interaction of employees significantly affects the KM implementation. Some barriers can be eliminated or alleviated as KM develops: these are usually found in firms that have established an appropriate KM system, including an IT mechanism and reward system. Managers may use both of these as a measure of KM system performance. However, some barriers unexpectedly worsen in the latter stages of KNM and hence, are important in companies with a well-developed business, solid organization, and a higher KM maturity level. Most of these are related to integration, and match the phenomena in KMM stages III and IV.

(3) Additional barriers to knowledge flow may occur.

Five factors affecting knowledge flow were discovered to occur through seldom discussed previously, such as technophobia (R12), authority (D27), lack of trust in the system (S32/R32), systematic knowledge documentation (M24), and intellectual property rights. Such barriers to knowledge flow were found in the second Round of the Delphi survey.

5.1. Technophobia (R12)

In our study, we found that technophobia appeared in each KMM stage, but it was more important and serious in the early stages, especially level II. This is not only related to personality traits, but also depends on contextual factors, such as organizational culture and firm characteristics. People naturally resist the need for or use of new methods, such as sharing knowledge with the KMS, because of unfamiliarity.

To deal with this barrier, we suggest three solutions that were proposed by the experts in our study: education before and during KM implementation, continuous communication, and giving KM activities high priority in organizations.

5.2. Lack of authority (D27)

Authority over the KMS is not the same in all organizations it is almost randomly assigned in each KM maturity level, but is especially important in the later stages. It is related to organizational structure, such as the hierarchy of the firm. KM enhances the value of the corporation by identifying the assets and expertise as well as efficiently managing resources. Security for KM is critical, as organizations have to protect their intellectual assets. Therefore, only authorized individuals may be permitted to execute some operations and functions [6]. Knowledge documents are involved in issues related to authority. Authority can be considered a dual channel for knowledge flow, and it can control this flow in an organization. For secure knowledge management, it is necessary to extend this determinant to confidentiality, trust, and privacy, which are also challenges for firms.

5.3. Lack of trust in the system (R33)

Most companies develop KMS by outsourcing, as this saves time and money. However, as a result, members do not trust KMS completely with respect to the leaking core knowledge or advanced techniques.

Another platform that is more secure but conservative for sharing knowledge is available: employees and directors can upload knowledge documents to a department server instead of a KMS. However, the platform of a department server is limited to users acquiring and uploading knowledge documents – it is only available to the LAN of the department.

5.4. Lack of systematic knowledge documentation (M24)

The results of our study showed that well organized and formatted documents as well as systematic knowledge documentation became more important as the KM system developed. Traditional mechanisms such as hard copy are not suitable for knowledge sharing, storing, and sorting in knowledge-based firms. Furthermore, a KM program without appropriate integration may cause disorder and confusion, leading to inefficiency. Although knowledge repositories are common in companies that have implemented KM activities, the knowledge documents they contain are often improperly structured or standardized. In order to deal with this barrier, some experts have proposed techniques for knowledge clustering or categorization, such as WordNet for document retrieval, browsing, text mining [29], and the Vector-space Model, Naïve Bayse, Neural Network, and Genetic Algorithms.

6. Conclusions

Although the literature about knowledge flow and KMM model has often been cited as significantly important, our study provided evidence that supported the concept that barriers to knowledge flow is different at various KMM levels. In addition, what and how KMM levels are different and associated with changing KM maturity levels was explored deeply.

6.1. Implications

Knowledge management cannot be regarded in a transient fashion. We have provided a holistic, systematic, and comprehensive framework with maturity levels for exploring the influences and changes to barriers to knowledge flow. Our work combined both horizontal and vertical perspectives as well as time factors and category of KM activities to observe overall barriers to knowledge flow. In practice, our study provides an approach to handling the barriers to knowledge flow at each KMM stage. In general, managers may just let barriers to knowledge flow take their course before detecting what kind of barriers they may meet. Thus, our findings not only provide a reference to help managers focus on and deal with the main problems that can arise during KM but can effectively and efficiently reduce the cost for firms as they seek to detect barriers to knowledge flow.

6.2. Research limitations

There are some limitations to survey research. First, although the results of descriptive analysis have shown the overall patterns of barriers to knowledge flow related to KM development, there is little we could do to determine the sources of participants' beliefs. Second, qualitative research is time-consuming, and it was difficult to collect data from a large number of firms at different KM maturity stages, resulting in a problem of insufficient data. Finally, questionnaires generally do not provide a rich picture of the complicated and interactive factors involved in KM implementations and contexts. Thus in-depth, face-to-face interviews and the Delphi method were added to our study, and they seem to have provided insights into issues related to KM.

Acknowledgements

This work was supported by National Science Council, Taiwan, ROC, under Grant NSC 96-2752-H-006-002-PAE. In addition, we particularly appreciate comments from the experts who participated in this research, especially the director of IBM in Taiwan and the data collection support from Tzu-Jung Huang, from the Institute of Information Management at National Cheng Kung University.

Appendix A. Interview instrument

Subject:	
Date:	
Interviewee:	
Researcher:	Professor Chinho Lin, Distinguished Professor, Institute of Information Management, National Cheng Kung University
	Ju-Chuan Wu, PhD candidate, Institute of Information Management, National Cheng Kung University
Main Topic:	Exploring Barriers to Knowledge Flow at Different Knowledge Management Maturity Stages
Background	This work aims to explore barriers to knowledge flow at different KM maturity level. Please first evaluate and identify the KM stage of your company by KNM (Knowledge Navigator Model) criteria, second to point out the common barriers to knowledge flow in your company based on classification of the revised CHAT model. And then please answer the questions as follows.
	Thanks for your participation and assistance.

A.1. Questions

1. How would you rate the importance of 5 dimensions of barriers to knowledge flow in different knowledge maturity level?

Dimension	Ranking (1–5)				
	KMM Level 1	KMM Level 2	KMM Level 3	KMM Level 4	KMM Level 5
(1) Knowledge characteristics					
(2) Knowledge source					

Appendix A (*Continued*)

Dimension	Ranking (1–5)				
	KMM Level 1	KMM Level 2	KMM Level 3	KMM Level 4	KMM Level 5
(3) Knowledge receiver					
(4) Contextual factor					
(5) Mechanisms					

2. Would you please pick the most important barriers (at least 10) in your company, and rate them from 1 to 10?

Dimension	Barriers to knowledge flow	Code	Importance	Propriety
Knowledge characteristics	1. Ambiguity	C01		
	2. Non-Validate Knowledge	C02		
Knowledge provider	3. Lack of time	S11		
	4. Fear of reducing job security	S12		
	5. Low awareness and realization of knowledge sharing	S13		
	6. Fear losing the ownership of intellectual property	S14		
	7. Not adequately rewarded	S15		
	8. Sense of self-worth	S16		
	9. Poor community skills	S21		
	10. Lack of trust in people	S22		
	11. Lack of trust in system (security)*	**S23**		
Knowledge receiver	12. NIH syndrome	R11		
	13. Technophobia*	**R12**		
	14. Lack of absorptive capability	R21		
	15. Lack of retentive capacity	R22		
	16. Lack of trust in knowledge	R31		
	17. Lack of trust in system(security)*	**R32**		
Contextual factor	18. Untrustworthiness	D11		
	19. Lack of contact time and interaction	D12		
	20. Differences in experience level (i.e. individual perceptions of approach ability)	D13		
	21. Difficult relationships	D14		
	22. Unawareness	D15		
	23. Culture and cultural characteristics	D21		
	24. Organizational structure (poor physical work environment/lack of spaces to share/excessive size of business units)	D22		
	25. Time and resource constraints	D23		
	26. Lack of organizational incentives	D24		
	27. Lack of leadership	D25		
	28. Lack of complete or standard regulation	D26		
	29. Authority*	**D27**		
	30. Lack of coordination between units (geographical dispersion/context differentiation/competitiveness)	D31		
	31. Different languages	D32		
	32. Overly technical terminology	D33		
Mechanism	33. Tangible mechanisms: telephone, discussion rooms or computer networks	M11		
	34. Failure to develop a transactive memory system	M12		
	35. Intangible mechanisms: unscheduled meetings, informal seminars, or coffee break conversations	M13		
	36. Lack of integration of IT systems and processes	M21		
	37. Lack of compatibility between diverse IT systems	M22		
	38. Unrealistic expectations of employees and mismatch with individual needs	M23		
	39. Lack of systematic knowledge documentation	M24		
	40. Employees lack familiarity and experience with new IT systems	M31		
	41. Lack of training regarding new IT systems	M32		
	42. Lack of communication with employees about the advantages of the new system	M33		

The bold entries are the additional determinants of knowledge flow from face-to-face interviews as shown in Table 4.

3. How would you rate the barriers of each dimension? 1–5 (strongly disagree, disagree, common, agree, strongly agree).

Dimension	Barriers to knowledge flow	Code	Rate
Knowledge characteristics	1. Ambiguity	C01	
	2. Non-Validate Knowledge	C02	
Knowledge source	3. Lack of time	S11	
	4. Fear of reducing job security	S12	
	5. Low awareness and realization of knowledge sharing	S13	
	6. Fear losing the ownership of intellectual property	S14	
	7. Not adequately rewarded	S15	
	8. Sense of self-worth	S16	
	9. Poor community skills	S21	
	10. Lack of trust in people	S31	
	11. Lack of trust in system (security)*	**S32**	
Knowledge receiver	12. NIH syndrome	R11	

Appendix A (*Continued*)

Dimension	Barriers to knowledge flow	Code	Rate
	13. Technophobia*	**R12**	
	14. Lack of absorptive capability	R21	
	15. Lack of retentive capacity	R22	
	16. Lack of trust in knowledge	R31	
	17. Lack of trust in system (security)*	**R32**	
Contextual factor	18. Untrustworthiness	D11	
	19. Lack of contact time and interaction	D12	
	20. Differences in experience level (i.e. individual perceptions of approach ability)	D13	
	21. Difficult relationships	D14	
	22. Unawareness	D15	
	23. Culture and cultural characteristics	D21	
	24. Organizational structure (Poor physical work environment/Lack of spaces to share/ Excessive size of business units)	D22	
	25. Time and resource constraints	D23	
	26. Lack of organizational incentives	D24	
	27. Lack of leadership	D25	
	28. Lack of complete or standard regulation	D26	
	29. Authority*	**D27**	
	30. Lack of coordination between units (geographical dispersion/context differentiation/ competitiveness)	D31	
	31. Different languages	D32	
	32. Overly technical terminology	D33	
Mechanism	33. Tangible mechanisms: telephone, discussion rooms or computer networks	M11	
	34. Failure to develop a transactive memory system	M12	
	35. Intangible mechanisms: unscheduled meetings, informal seminars, or coffee break conversations	M13	
	36. Lack of integration of IT systems and processes	M21	
	37. Lack of compatibility between diverse IT systems	M22	
	38. Unrealistic expectations of employees and mismatch with individual needs	M23	
	39. Lack of systematic knowledge documentation	M24	
	40. Employees lack familiarity and experience with new IT systems	M31	
	41. Lack of training regarding new IT systems	M32	
	42. Lack of communication with employees about the advantages of the new system	M33	

The bold entries are the additional determinants of knowledge flow from face-to-face interviews as shown in Table 4.

4. Please define the main barriers in each KMM stages, and in your company.

Barriers to knowledge flow	Code	Research finding					Your opinion				
		KMM					KMM				
		I	II	III	IV	V	I	II	III	IV	V
1. Ambiguity	C01										
2. Non-Validate Knowledge	C02										
3. Lack of time	S11										
4. Fear of reducing job security	S12										
5. Low awareness and realization of knowledge sharing	S13										
6. Fear losing the ownership of intellectual property	S14										
7. Not adequately rewarded	S15										
8. Sense of self-worth	S16										
9. Poor community skills	S21										
10. Lack of trust in people	S31										
11. Lack of trust in system (security)*	**S32**										
12. NIH syndrome	R11										
13. Technophobia*	**R12**										
14. Lack of absorptive capability	R21										
15. Lack of retentive capacity	R22										
16. Lack of trust in knowledge	R31										
17. Lack of trust in system (security)*	**R32**										
18. Untrustworthiness	D11										
19. Lack of contact time and interaction	D12										
20. Differences in experience level (i.e. individual perceptions of approach ability)	D13										
21. Difficult relationships	D14										
22. Unawareness	D15										
23. Culture and cultural characteristics	D21										
24. Organizational structure (poor physical work environment/lack of spaces to share/excessive size of business units)	D22										
25. Time and resource constraints	D23										
26. Lack of organizational incentives	D24										
27. Lack of leadership	D25										
28. Lack of complete or standard regulation	D26										
29. Authority*	**D27**										
30. Lack of coordination between units (geographical dispersion/context differentiation/competitiveness)	D31										

Appendix A (*Continued*)

Barriers to knowledge flow	Code	Research finding KMM I	II	III	IV	V	Your opinion KMM I	II	III	IV	V
31. Different languages	D32										
32. Overly technical terminology	D33										
33. Tangible mechanisms: telephone, discussion rooms or computer networks	M11										
34. Failure to develop a transactive memory system	M12										
35. Intangible mechanisms: unscheduled meetings, informal seminars, or coffee break conversations	M13										
36. Lack of integration of IT systems and processes	M21										
37. Lack of compatibility between diverse IT systems	M22										
38. Unrealistic expectations of employees and mismatch with individual needs	M23										
39. Lack of systematic knowledge documentation	M24										
40. Employees lack familiarity and experience with new IT systems	M31										
41. Lack of training regarding new IT systems	M32										
42. Lack of communication with employees about the advantages of the new system	M33										

The bold entries are the additional determinants of knowledge flow from face-to-face interviews as shown in Table 4.

5. Please help to confirm the tendency of the barriers to knowledge flow in each KMM level, and in your company.

Tendency	Barriers	Dimension	Agree(v) or disagree(x)	Your opinion
Existence	Lack of time (S11) Low awareness and realization of knowledge sharing (S13) Fear of losing the ownership of intellectual property (S14) Lack of leadership (D25) Unrealistic expectation of employees and mismatch with individual needs (M23)	People		
Decline	Not adequately rewarded (S15) Lack of contact time and interaction (D12) Culture and cultural characteristics (D21) Lack of organizational incentives (D24) Lack of complete or standard regulation (D26), Overly technical terminology (D33) Failure to develop a transitive memory system (M21) Employees lack familiarity and experience with new IT systems (M31)	Mechanism development		
Increase	Authority (D27) Lack of coordination between units (D31) Lack of integration of IT systems and processes (M21) Lack of compatibility between diverse IT systems (M22) Lack of systematic knowledge documentation (M24)	Mechanism integration		
Random	Technical phobia (R12) Lack of trust in system (S32) Untrustworthiness (D11)			

6. Please comment the additional factors as following table shows, and rate them.

Additional findings	Importance	Your comment
Technophobia (R12)		
Authority (D27)		
Lack of trust in system (R33)		

References

[1] H.J. Ahn, H.J. Lee, K. Cho, S.J. Park, Utilizing knowledge context in virtual collaborative work, Decision Support Systems 39 (4), 2005, pp. 563–582.

[2] M. Alavi, T.R. Kayworth, D.E. Leidner, Empirical examination of the influence of organizational culture on knowledge management practices, Journal of Management Information Systems 22 (3), 2005, pp. 191–224.

[3] AMR Research, The Knowledge Management Spending Report 2007–2008, 2007, http://www.amrresearch.com/Content/View.asp?pmillid=20744 (accessed on 11 August 2008).

[4] L.G.A. Beesley, C. Cooper, Defining knowledge management (KM) activities: towards consensus, Journal of Knowledge Management 12 (3), 2008, pp. 48–62.

[5] R. Benson, F. Stacie, B. Richard, Overcoming barriers to knowledge sharing in virtual teams, Organizational Dynamics 36 (3), 2007, pp. 259–273.

[6] E. Bertino, L.R. Khan, R. Sandhu, B. Thuraisingham, Secure knowledge management: confidentiality, trust, and privacy, IEEE Transactions on Systems, Man and Cybernetics, Part A 36 (3), 2006, pp. 429–438.

[7] G. Bock, R.W. Zmud, Y. Kim, J. Lee, Behavioral intention formation in knowledge sharing: examining the roles of extrinsic motivators, social-psychological forces, and organizational climate, MIS Quarterly 29 (1), 2005, pp. 87–111.

[8] D.P. Brandon, A.B. Hollingshead, Transactive memory systems in organizations: matching tasks, expertise, and people, Organization Science 15 (6), 2004, pp. 633–644.

[9] T.C. Chou, P.L. Chang, Y.P. Cheng, C.T. Tsai, A path model linking organizational knowledge attributes, information processing capabilities, and perceived usability, Information & Management 44 (4), 2007, pp. 408–417.

[10] K.C. Desouza, Strategic contributions of game rooms to knowledge management: some preliminary insights, Information & Management 41 (1), 2003, pp. 63–74.

[11] Y. Duan, W. Nie, E. Coakes, Identifying key factors affecting transnational knowledge transfer, Information & Management 47 (7/8), 2010, pp. 356–363.

[12] W. He, Q. Qiao, K. Wei, Social relationship and its role in knowledge management systems, Information & Management 46 (3), 2009, pp. 178–180.

[13] R.M Henry, G.E. McCray, R.L. Purvis, T.L. Roberts, Exploiting organizational knowledge in developing IS project cost and schedule estimate: an empirical study, Information & Management 44 (6), 2007, pp. 598–612.

[14] P.J. Hsieh, B. Lin, C. Lin, The construction and application of knowledge navigator model (KNM™): an evaluation of knowledge management maturity Original Research Article, Expert Systems with Applications 36 (2), 2009, pp. 4087–4100.

[15] M.C. Jones, M. Cline, S. Ryan, Exploring knowledge sharing in ERP implementation: an organizational culture framework, Decision Support Systems 41 (2), 2006, pp. 411–434.

[16] E.M Kamhawi, The three tiers architecture of knowledge flow and management activities, Information and Organization 20 (3/4), 2010, pp. 169–189.

[17] M. Kazemi, M.Z. Allahyari, Defining a knowledge management conceptual model by using MADM, Journal of Knowledge Management 14 (6), 2010, pp. 872–890.

[18] K.U. Koskinen, Metaphoric boundary objects as coordinating mechanisms in the knowledge sharing of innovation processes, European Journal of Innovation Management 8 (3), 2005, pp. 323–335.

[19] J. Lee, E. Suh, J. Hong, A maturity model based CoP evaluation framework: a case study of strategic CoPs in a Korean company, Expert Systems with Applications 37 (3), 2010, pp. 2670–2681.

國立雲林科技大學
101 學年度博士班招生考試試題

系所別：資訊管理系
科　目：資訊科技文獻

本試題共分A、B兩部分，各包括一篇論文以及相關的問題，作答時請注意各題之比例配分並清楚標示題號。

Part A: 50%

Title: Effective Semantic Annotation by Image-to-Concept Distribution Model
Questions:

1. What is the main research problem mentioned in this study? Does it matter to image annotation? What is your opinion on this issue? 10%
2. In this paper, the authors propose an Image-to-Concept Distribution Model (AICDM) by making use of entropy, *tf-idf* and association rules to achieve high annotation quality. Please discuss the research methods and findings. 20%
3. Precision, recall, and execution time are used as the method of comparisons between the proposed AICDM and other well-known annotators. Usually, precision and recall scores are not discussed in isolation, and both are usually combined into a single measure, such as the F-measure. Describe it. 10%
4. After reading this paper, what other visual features in your opinion could be explored to enhance the annotation quality in the future study? 10%

Part B: 50%

The Growing Harm of Not Teaching Malware
請依據文章內容以中文回答下列問題：
1. 請說明本篇論文的主要論點。(10%)
2. 請比較今昔惡意程式所引起的問題。(10%)
3. 作者在本文中強調的風險主要是什麼？(10%)
4. 作者認為對付網路上惡意攻擊的最好方法是什麼？(10%)
5. 你是否同意作者的說法？試申論之。(10%)

Effective Semantic Annotation by Image-to-Concept Distribution Model

Ja-Hwung Su, Chien-Li Chou, Ching-Yung Lin, and Vincent S. Tseng, *Member, IEEE*

***Abstract*—Image annotation based on visual features has been a difficult problem due to the diverse associations that exist between visual features and human concepts. In this paper, we propose a novel approach called Annotation by Image-to-Concept Distribution Model (AICDM) for image annotation by discovering the associations between visual features and human concepts from image-to-concept distribution. Through the proposed image-to-concept distribution model, visual features and concepts can be bridged to achieve high-quality image annotation. In this paper, we propose to use "visual features", "models", and "visual genes" which represent analogous functions to the biological chromosome, DNA, and gene. Based on the proposed models using entropy, tf-idf, rules, and SVM, the goal of high-quality image annotation can be achieved effectively. Our empirical evaluation results reveal that the AICDM method can effectively alleviate the problem of visual-to-concept diversity and achieve better annotation results than many existing state-of-the-art approaches in terms of precision and recall.**

***Index Terms*—Entropy, image annotation, image-to-concept distribution, tf-idf.**

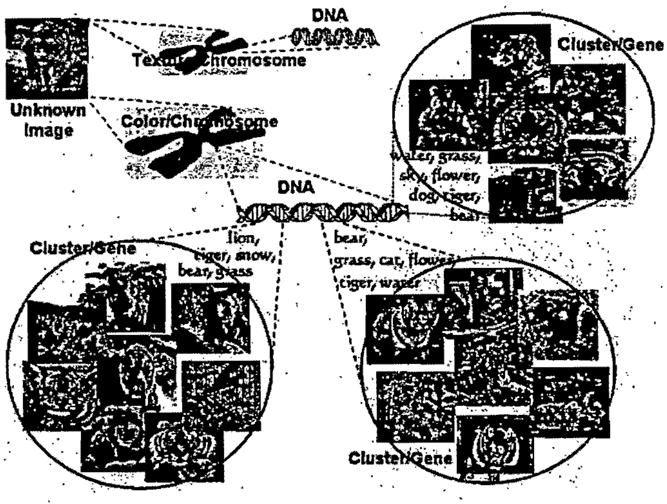


Fig. 1. Basic idea of the proposed AICDM.

I. Introduction

ADVANCED digital capturing technologies have led to the explosive growth of image data. To retrieve the desired images from a huge amount of image data, textual query is handier to represent her/his interest than providing visually similar images for query. Most existing successful textual-based image retrieval relies heavily on the related image caption terms, e.g., file-names, categories, annotated keywords, and other manual descriptions. To caption the images effectively, in the last decade, extensive image understanding techniques have been developed to explore semantic concept of images. But, due to the significant diversity of a large amount of image data in daily life, effective image annotation is still a very challenging and open problem. Diverse visual feature versus concept associations indicate that the same visual feature is frequently shared by a set of concepts. The challenge is that the related terms are so diverse that the annotator could not annotate the unknown image accurately. In existing annotation work, this problem, namely the diverse visual-to-concept associations, occurs so frequently that many annotation results are not satisfactory for human users.

To address this problem, in this paper, we propose novel visual-to-concept distribution models that integrate the methods of entropy, $tf-idf$ and association rules to enhance the annotation quality. In molecular biology, genes locating on different chromosomes have similar functions due to the high similarity of their DNA sequences. This is useful for predicting the specific function for a gene. Based on this notion, the purpose of this paper is to annotate the image by discovering the representative and discriminative visual features alike the genes hidden in the images. Fig. 1 is an example for the basic idea of our proposed AICDM. In Fig. 1, we consider each image has a specific number of features to be extracted—similar to chromosome. On each visual feature, a set of models can be applied to divide image collections into several different cluster sets. A specific model of a visual chromosome/feature can be considered as a DNA. For each DNA, a "visual gene" is the visual pattern of a cluster, which includes a set of visually-correlated images of a model on a visual feature and a set of caption terms associated with them. Similar to the biological gene, each "visual gene" carries the information, i.e., the caption terms that have been learned from training corpus. Our intent behind this idea is to identify the conceptual distinctness of each gene. According to the discriminative genes, the image-to-concept distribution model is constructed. For an unknown test image, we shall then

Manuscript received November 03, 2010; revised February 28, 2011; accepted March 08, 2011. Date of publication March 17, 2011; date of current version May 18, 2011. This work was supported by National Science Council, Taiwan, R.O.C. under grants NSC99-2631-H-006-002 and NSC99-2218-E-006-001. The associate editor coordinating the review of this manuscript and approving it for publication was Dr. Zhu Liu.

J.-H. Su and V. S. Tseng are with the Department of Computer Science and Information Engineering, National Cheng Kung University, Tainan 701, Taiwan (e-mail: bb0820@ms22.hinet.net; tsengsm@mail.ncku.edu.tw).

C.-L. Chou is with the Department of Computer Science and Information Engineering, National Chiao Tung University, Hsinchu, Taiwan (e-mail: fallwinds@gmail.com).

C.-Y. Lin is with IBM T. J. Watson Research Center, Hawthorne, NY 10532 USA (e-mail: chingyung@us.ibm.com).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TMM.2011.2129502

classify them to find out the likelihood that they are composed of a certain gene. Then, the concept terms of genes are associated to this unknown images based on these genes.

In this paper, we propose four types of models, which can be classified into three categories: 1) from viewpoint of individual images, we adopt tf (term frequency) and entropy to weight the concept terms and genes, respectively; 2) from viewpoint of image sets, we adopt association-rule confidence and *idf* (inverse document frequency) to weight the concept terms and genes; and 3) by integrating tf, idf, entropy and association rules, we apply late fusion using support vector machines (SVM) [2] to achieve high-quality image annotation. The empirical evaluations on several image sets reveal that our proposed Annotation by Image-to-Concept Distribution Model (AICDM) is very promising on semantic annotation by measuring precision and recall of the annotation accuracy, comparing to several existing algorithms. The remaining of this paper is organized as follows. Several prior works are reviewed in Section II. In Section III, we present the proposed method in detail. The related experimental evaluations are described in Section IV. Finally, the conclusion and future work are stated in Section V.

II. Related Work

In general, image annotation work can be categorized into several types.

Classification-Based Annotation: The first type is the classification-based annotation. In the past, some studies treated annotation as classification using multiple classifiers. Yang *et al.* [24] proposed a region-based annotation method by using SVM. This study presented an extended SVM namely asymmetrical SVM to infer the caption terms of images. Nasierding *et al.* [9] adopted multi-classifier to achieve image annotation by integrating clustering and classification methods. Similarly, Wu *et al.* [18] optimized the bag-of-words to preserve semantic of images. In addition, Bayesian classifier was built to annotate images by integrating regional and global features [10]. Fan *et al.* [5] proposed a structured max-margin learning algorithm to conduct effective inter-related classifiers to support image annotation.

Probabilistic-Based Annotation: The second type is the probabilistic-based annotation. Probabilistic models are constructed by estimating the correlations between images and concepts. Li *et al.* [7] computed the relational probabilities between images and concepts by multi-statistical models, e.g., 2-D Hidden Markov Model, Gaussian, and Gamma distributions. Lavrenko *et al.* [6] calculated the related probabilities between segmentations and concepts by Gaussian Mixture Function. Pan *et al.* [11] developed Mixed Media Graph (MMG) model to annotate the image by Cross-modal Correlation Discovery (CCD) algorithm to calculate the affinities of caption terms and regions. Tang *et al.* [14] proposed the multi-graph-based label propagation approach that integrates multiple instance learning and single instance learning to tag the unknown image.

Retrieval-Based Annotation: The third type is the retrieval-based annotation. The basic notion behind retrieval-based annotation is that semantic-relevant images are composed of similar visual features. Wang *et al.* [22] proposed the AnnoSearch system to bridge the semantic gap by Search Result Clustering (SRC) [25]. Wang *et al.* [23] annotated an image by both of visual and textual search. By using social images with tags and

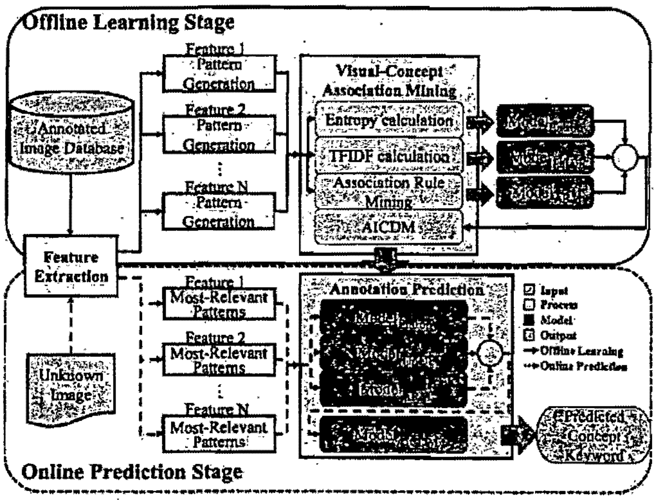


Fig. 2. Framework of the proposed AICDM.

user-generated content, Wu *et al.* [17] presented a retrieval-based method to tag images effectively.

In addition to the above three types of annotation methods that are mainly based on the content modeling, the other type is to use more textual information to enhance the annotation quality [15]. Wong *et al.* [20] made use of the additional metadata, such as aperture, exposure time, subject distance, focal length, and fire activation, to tag the images. Tseng *et al.* [16] integrated decision tree and MMG based on textual and visual information to annotate the web images. Wu *et al.* [19] proposed Flickr distance to achieve effective image annotation. In fact, the Flickr distance work and our proposed method have different advantages. The proposed method in this paper is an extended work of [12]. For the Flickr distance work, it is effective on resolving the problem of concept appearance variation by using spatial information [21]. For our proposed method, by discovering the representative and discriminative patterns, it is effective to alleviate the annotation problem that a feature may occur frequently in many concepts.

III. Proposed Approach

A. Overview of the Proposed Image Annotator

The so-called diverse visual-to-concept associations indicate that similar visual features may frequently occur in different concepts. From another point of view, it says that a semantic concept contains different visual features. In real applications, image annotators encounter difficulties in these diverse associations between visual features and human concepts. To address this problem, in this paper, we propose novel visual-to-concept distribution models that integrate the methods of entropy, $tf-idf$ and association rules to achieve high annotation quality. As shown in Fig. 2, the whole procedure can be decomposed into two stages, namely *offline learning* and *online prediction*.

1) Offline Learning Stage: Overall this stage contains three main sub-procedures, called *feature extraction*, *pattern generation*, and *model construction*.

- **Feature Extraction**: In this paper, six visual features are extracted from the images, including Scalable Color Descriptor, Color Layout Descriptor, Homogeneous Texture

Descriptor, Edge Histogram Descriptor, Grid Color Moment, and Gabor Wavelet Moment, whose dimensionalities are 256, 12, 62, 80, 225, and 72, respectively.

- **Pattern Generation**: After feature extraction, the annotated images are grouped into a set of visual clusters feature by feature. A cluster can be regarded as a representative and discriminative gene hidden in the training images. In other words, images can be described by six visual features.
- **Model Construction**: From the generated patterns, term frequency and inverse document frequency ($tf-idf$) and cluster entropy are calculated to construct Model_{tf-idf} and $\text{Model}_{entropy}$, respectively. Also, association rules are mined to generate Model_{ARM} (Association Rule Mining). Finally, three individual models are integrated into a fusion model, Model_{AICDM}, by SVM [2].

2) Online Prediction Stage: In this stage, the major aim is to identify the concepts of an unknown image using the proposed models. First, for an unknown image, the most-relevant clusters/patterns are determined feature by feature. Through the most-relevant patterns, potential caption terms can be predicted by the modeled relations between visual features and semantic concepts.

B. *Offline Learning*

1) Pattern Generation: Before constructing the proposed models, the annotated images are grouped by calculating visual distances. In this work, images are clustered by the well-known k-means algorithm. Thereupon we can obtain a set of clusters, also called patterns or genes in this paper, for each visual feature. A cluster contains a set of images and an image is annotated by a set of keywords. Let us take Fig. 3 as an example. Assume that the images are grouped into five clusters $\{C_1, C_2, C_3, C_4, C_5\}$ by Scalable Color Descriptor, and each image is projected as a set of keywords. In Fig. 3, a box stands for a set of concept terms related to an image. An issue of concern in this work is the quality of clustering since it actually makes a significant impact on the quality of online prediction. To make the clustering quality robust, we perform the validation methods proposed by [13]. After clustering, for each feature, the images are grouped into a set of clusters. Each cluster is viewed as a pattern/gene. For example, the related pattern set for scalable color descriptors is $\{C_1, C_2, \ldots, C_5\}$.

2) Basic Idea: From the generated clusters, we can observe that images in a cluster are very similar on the visual features but containing a number of different concepts. This is a big problem called diverse visual-to-concept associations to confound current annotators. From the bioinformatics point of view, two images may be similar if they share similar visual patterns that are considered as visual genes in this work. Unfortunately, a visual gene perhaps contains lots of concepts. It relates to three important issues: 1) How important is a caption term in a gene, 2) How important is a gene among all visual genes, and 3) How associative is a term-gene pair. To answer these questions, we propose a novel solution that integrates caption term frequency, gene entropy, and association visual-to-concept rule to achieve the high retrieval quality of image annotation.

3) Construction of $Model_{entropy}$: As elaborated above, our intention is to identify the importance of a caption term and a

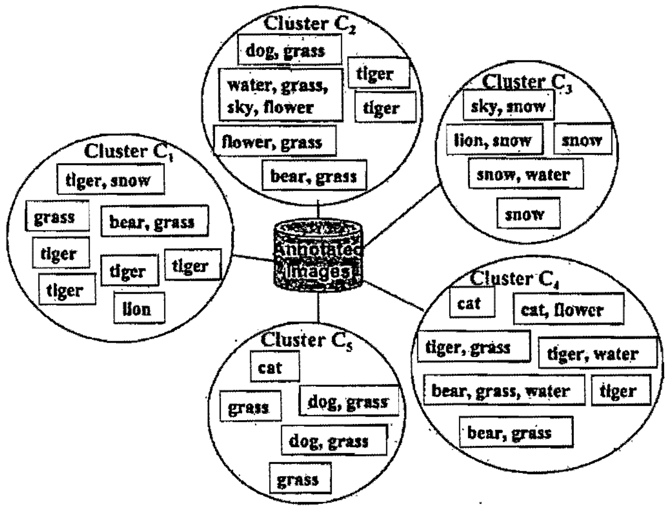


Fig. 3. Example of visual clusters containing the related concepts.

pattern by calculating caption term frequency and pattern entropy. The major idea is that, the higher the frequency of a caption term, the more representative it is. In contrast, if a large number of caption terms occur in a cluster, the related entropy would be too high to disambiguate visual concepts. That is, entropy can be viewed as a local weight for a gene. According to this notion, two related measures [12], called Term Frequency (tf) and Entropy, are defined as follows.

Definition 1: Consider a training data set IDB $= \{img_1, img_2, \ldots, img_k\}$ is divided into t clusters, $\{C_1, C_2, \ldots, C_t\}$, and there are y unique caption terms $\{cp_1, cp_2, \ldots, cp_y\}$. Assume that a cluster contains several images and each image is assigned several caption terms. Hence a cluster can be viewed as a collection of caption terms, $C_j = \cup cp_i$. The entropy of the j^{th} cluster/gene can be defined as

$$Entropy^j = \sum_{cp_i \in C_j} \left[\frac{tf^j_{cp_i}}{\sum_{cp_v \in C_j} tf^j_{cp_v}} \log \left(\frac{\sum_{cp_v \in C_j} tf^j_{cp_v}}{tf^j_{cp_i}} \right) \right]. \tag{1}$$

where $tf^j_{cp_i}$ stands for the frequency of caption term cp_i in the jth cluster. For example, based on Fig. 3, the frequency set of {grass, dog, cat} for C_5 is {4, 2, 1} and $Entropy^5$ is $4/7^* \log(7/4) + 2/7^* \log(7/2) + 1/7^* \log(7/1) = 0.415$. Thus, the entropy set is $\{Entropy^1, Entropy^2, Entropy^3, Entropy^4, Entropy^5\} = \{0.59, 0.778, 0.466, 0.755, 0.415\}$.

4) Construction of $Model_{tf-idf}$: Similar to the above model, tf is also generated first. Another way to determine the discrimination of a gene is inverse document frequency, namely idf. In this paper, the idf of the jth cluster/gene can be defined as the following [12].

Definition 2: Following the above definitions, the "inverse document frequency (idf)" for the jth cluster/pattern is

$$idf^j = \log \left(\frac{y}{\sum_{1 \le g \le y} df^j_{cp_g}} \right) \tag{2}$$

TABLE I
DEFINITIONS OF VISUAL PATTERN SETS

Feature	Pattern Set
Scalable Color Descriptor	KC=$\{C_1, C_2, \ldots, C_{kc}\}$
Color Layout Descriptor	KL=$\{L_1, L_2, \ldots, L_{kl}\}$
Homogeneous Texture Descriptor	KH=$\{H_1, H_2, \ldots, H_{kh}\}$
Edge Histogram Descriptor	KE=$\{E_1, E_2, \ldots, E_{ke}\}$
Grid Color Moment	KG=$\{G_1, G_2, \ldots, G_{kg}\}$
Gabor Wavelet Moment	KW=$\{W_1, W_2, \ldots, W_{kw}\}$

where

$$df^j_{cp_g} = \begin{cases} 1, & if\ C_j\ contains\ caption\ cp_g \\ 0, & otherwise. \end{cases}$$

In this model, if the pattern/gene contains most of unique caption terms, it would be a general pattern/gene. Therefore, its discrimination with respect to *idf* is low. Let us take an example based on Fig. 3. The set of unique caption terms in this example is {tiger, grass, bear, lion, snow, sky, flower, water, cat, dog}. For cluster C_1, it contains the caption term set {tiger, grass, bear, lion, snow}. The *idf* of C_1 is $\log(10/5) = 0.301$. For cluster C_2, the *idf* of C_2 is $\log(10/7) = 0.155$. In this case, C_1 is more discriminative than C_2. Overall *idf* can be viewed as the global weight for a gene. Thus, the final *idf* set for $\{C_1, C_2, C_3, C_4, C_5\}$ is {0.301, 0.155, 0.398, 0.222, 0.523}.

5) Construction of Model$_{ARM}$: In summary, the above two models are constructed feature by feature. That is, regarding Table I, six entropy models and six $tf-idf$ models are generated. In contrast to the above models, the main concern of Model$_{\text{ARM}}$ is to discover the associations between visual features and concept keywords by considering all features simultaneously. Before mining the associations, it is necessary to define the items. To fit association mining, a pattern or a concept keyword is regarded as an item and an image perhaps contains a set of keywords (caption terms). Furthermore, in this model, a transaction divided can be defined as follows.

Definition 3: Based on the definitions in Definition 1 and Table I, the ith transaction T_i for the kth image img_k is

$$T_i = \langle \{C_{t_1}, L_{t_2}, H_{t_3}, E_{t_4}, G_{t_5}, W_{t_6}\}, \{cp_g\}\rangle \quad (3)$$

where

$$C_{t_1} \in KC,\ L_{t_2} \in KL,\ H_{t_3} \in KH,\ E_{t_4} \in KE,\ G_{t_5} \in KG,\ W_{t_6} \in KW$$

and cp_g is one of the concept keywords related to img_k.

For example, assume image$_k$ contains two keywords {tiger, grass}. Thus, the referred transactions are $\langle\{C_2, L_1, H_4, E_5, G_1, W_2\}, \{\text{tiger}\}\rangle$ and $\langle\{C_2, L_1, H_4, E_5, G_1, W_2\}, \{\text{tiger}\}\rangle$ where the set of patterns for img_k is $\langle\{C_2, L_1, H_4, E_5, G_1, W_2\}, \{\text{grass}\}\rangle$. Finally, the annotated image database can be transformed into a transaction database. After database transformation, discovering the association rules from transaction data is our next intention in this work. From the transactions, a rule and related confidence can be defined in the following.

Definition 4: Consider that there are n rules in the rule set $\{R_1, R_2, \ldots, R_n\}$ mined from the transaction database. Thus, a rule in the rule set can be defined as

$$R_i : Feature\ Patterns \rightarrow Concept\ Keyword. \quad (4)$$

The confidence of rule R_i can be defined as

$$Confidence(R_i) = \frac{Sup(Feature\ Patterns \cup Concept\ Keyword)}{Sup(FeaturePatterns)} \quad (5)$$

where the Sup(itemset) is the normalized frequency of the itemset in transaction database. For example, the rule $R_1 : \{C_2, E_5, G_1, W_2\} \rightarrow \{\text{tiger}\}$ indicates that the image whose features can be assigned to the pattern set $\{C_2, E_5, G_1, W_2\}$ always contains a concept keyword, "tiger". The confidence of rule R can be calculated by (5):

$$Confidence(R_1) = \frac{Sup(\{C_2, E_5, G_1, W_2, \text{tiger}\})}{Sup(\{C_2, E_5, G_1, W_2\})}$$

where $Sup(\{C_2, E_5, G_1, W_2, \text{tiger}\})$ indicates the count of itemset $\{C_2, E_5, G_1, W_2, \text{tiger}\}$ and $Sup(\{C_2, E_5, G_1, W_2\})$ indicates the count of itemset $\{C_2, E_5, G_1, W_2\}$.

In addition to the confidence value of a rule, another considerable factor τ_{R_i} named *pattern-concept count* is how many concept keywords are implied by the same Feature Patterns set. The basic idea is that, if a feature itemset is shared with lots of concept keywords, the discrimination of the rule is relatively low. From another viewpoint, if lots of rules contain the same feature itemset, the related weights are low. Thus, for each rule, we count the number of implied keywords. For example, suppose that three rules

$$R_1 : \{C_2, E_5, G_1, W_2\} \rightarrow \{\text{tiger}\},$$
$$R_2 : \{C_2, E_5, G_1, W_2\} \rightarrow \{\text{grass}\} \text{ and}$$
$$R_3 : \{C_1, E_3, G_5, W_1\} \rightarrow \{\text{tiger}\}$$

are mined from the transaction database. The set $\{C_2, E_5, G_1, W_2\}$ implies two keywords, "tiger" and "grass". Thus, the pattern-concept counts τ_{R_1} and τ_{R_2} are both 2. Comparatively, the set $\{C_1, E_3, G_5, W_1\}$ implies only one keyword, "tiger". Therefore, the related pattern-concept count τ_{R_3} is 1. From discrimination point of view, R_3 is better than R_1 and R_2. At last, the rules, confidences, and pattern-concept counts are all stored into rule database.

C. Online Prediction for Annotation

The prediction procedure starts when an unknown image QI is submitted to this system. First, for each feature, the most-relevant clusters are determined by calculating visual similarities/distances. Assume that the most-relevant cluster set CS to QI is determined by visual distance calculations. The visual similarity (visual distance) between the unknown image and the jth cluster is defined as dis^j in this paper. Actually, the most-relevant clusters can be regarded as a kind of genes for the unknown image. Once the genes of the unknown image are determined, three prediction models are triggered to predict the

534 IEEE TRANSACTIONS ON MULTIMEDIA, VOL. 13, NO. 3, JUNE 2011

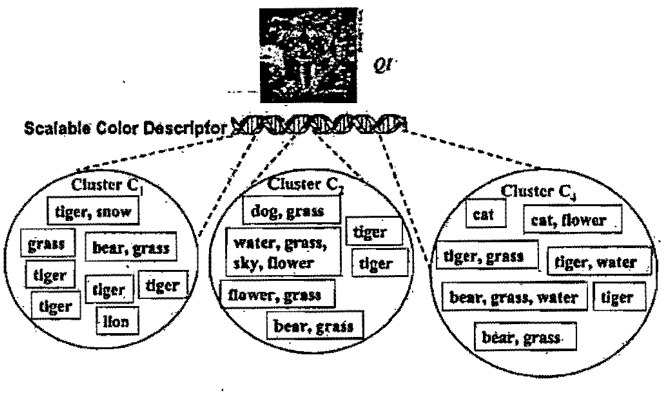


Fig. 4. Example of three relevant clusters to the unknown image.

potential caption terms. In our current system, the number of the most-relevant clusters is determined by experimental evaluations based on training set.

1) Prediction by $Model_{entropy}$: In this model, our intent is to weight caption terms by using gene entropy and caption term frequency. The major notion is that, if the caption term occurs frequently in a gene with low entropy, its referred degree would be high. Otherwise, its degree would be low. Finally, the caption terms are ranked by the related degrees. In this paper, the entropy-based degree [12] is defined as

$$EDegree_{cp_x} = \sum_{C_j \in CS} \left[\left(\frac{tf^j_{cp_x}}{\sum_{cp_v \in C_j} tf^j_{cp_v}} \right) \times \frac{1}{Entropy^j} \times \left(\frac{\left(\sum_{1 \le k \le |IDB|} dis^k\right)}{dis^j} \right) \right] \quad (6)$$

where $1 \leqq x \leqq y$. Afterwards the EDegree is normalized. The normalization is defined as

$$NormEDegree_{cp_x} = \frac{EDegree_{cp_x}}{\sum_{i=1}^{y} EDegree_{cp_i}}. \quad (7)$$

The EDegrees referred to the selected six features are aggregated and normalized as the final degrees for a caption term. Let us take an example based on Figs. 3 and 4. Assume that the most-relevant cluster/gene set for an unknown image QI is $\{C_1, C_2, C_4\}$. Accordingly, these three most-relevant clusters contain 21 images and ten unique caption terms. If the referred distance set for $\{dis^1, dis^2, dis^4\}$ is {150, 500, 250} and the sum of distances for $\{dis^1, dis^2, dis^3, dis^4, dis^5\}$ is 2700, the normalized distance set is {18, 5.4, 10.8}. Therefore, the entropy set of $\{C_1, C_2, C_4\}$ is {0.59, 0.778, 0.755}. Thus, the EDegree for {tiger} is ((5/10)*(1/0.59)*(18)) + ((2/12)*(1/0.778)*(5.4))+((3/13)*(1/0.755)*(10.8)) = 19.714. Finally, the entropy-based degree set for caption term set {tiger, grass, bear, lion, snow, sky, flower, water, cat, dog} is {19.714, 11.717, 5.831, 3.051, 3.051, 0.578, 2.257, 2.78, 2.202, 0.578}. In this example, the correct caption term set {tiger, grass} regarding Fig. 1 is successfully inferred from top 2 results.

2) Prediction by $Model_{tf-idf}$: To weight caption terms by considering the global weight, we adopt idf to reveal the degrees of the caption terms in the most-relevant genes. The major notion behind this model is that, if the caption term occurs frequently in a gene with high idf, its related degree would be high. Otherwise, its degree would be low. At last, the caption terms are ranked by the related degrees. We define the idf-based degree [12] as

$$FDegree_{cp_x} = \sum_{C_j \in CS} \left[\left(\frac{tf^j_{cp_x}}{|C_j|} \right) \times idf^j \times \left(\frac{\left(\sum_{1 \le k \le |IDB|} dis^k\right)}{dis^j} \right) \right] \quad (8)$$

where $1 \leqq x \leqq y$. Afterwards the EDegree is normalized. The normalization is defined as

$$NormFDegree_{cp_x} = \frac{FDegree_{cp_x}}{\sum_{i=1}^{y} FDegree_{cp_i}}. \quad (9)$$

At last, the FDegrees referred to the selected six features are aggregated and normalized as the final degrees for a caption term. For example, based on above examples, for caption term "tiger", the occurring cluster set is $\{C_1, C_2, C_4\}$ and the related FDegree is (5/5*0.301*2700/150) + (2/7*0.155*2700/500)+(3/6*0.222*2700/250) = 6.854. The final FDegree set for {tiger, grass, bear, lion, snow, sky, flower, water, cat, dog} is {6.854, 3.839, 1.998, 1.08, 1.08, 0.119, 0.637, 0.918, 0.799, 0.119}. Therefore, the correct caption term set {tiger, grass} is successfully derived by this model.

3) Prediction by Fusion $Model_{ARM}$: In addition to the above degrees, the confidences of rules are adopted to reveal the degrees of the concept keywords in the most-relevant pattern. The major notion behind this prediction is that, if a concept keyword occurs in lots of rules, it is a general caption term in the global feature space. As a result, its related degree is high. In this prediction, the six patterns for an unknown image QI are first determined for six selected features, respectively. Then the matched association rules for QI are found. Based on Definition 4, the matched rule set RQI can be defined as $RQI = \cup\{R^{QI}_i\}$, where R^{QI}_i denotes the matched rule for QI. Then the length of rule R^{QI}_i, defined as $len(R^{QI}_i)$, is $|FeaturePatterns|$. For example, the $len(R^{QI}_i)$ of rule $\{C_2, E_5, G_1, W_2\} \rightarrow$ {tiger} is 4 because there are four items in the left-hand side of the rule. In this work, we have to find the maximum matching rules. That is, if $len(R^{QI}_i)$ is maximum among all matching rules, the rule R^{QI}_i is added into the longest rule set $LRS(RQI)$. Moreover, the related sub-rule sets, which are the combinations of a feature pattern and a caption term, are chosen. For example, there is a maximum matching rule R^{QI}_1: $\{C_2, E_5, G_1, W_2\} \rightarrow$ {tiger}, and the related sub-rule set $sub(R^{QI}_1)$ is $\{\{C_2\} \rightarrow$ {tiger}, $\{E_5\} \rightarrow$ {tiger}, $\{G_1\} \rightarrow$ {tiger}, $\{W_2\} \rightarrow$ {tiger}}. After determining the matching rules and the related sub-rules, the degrees of concept keywords are calculated by the pattern-concept counts of these rules. Finally, the concept keywords are ranked

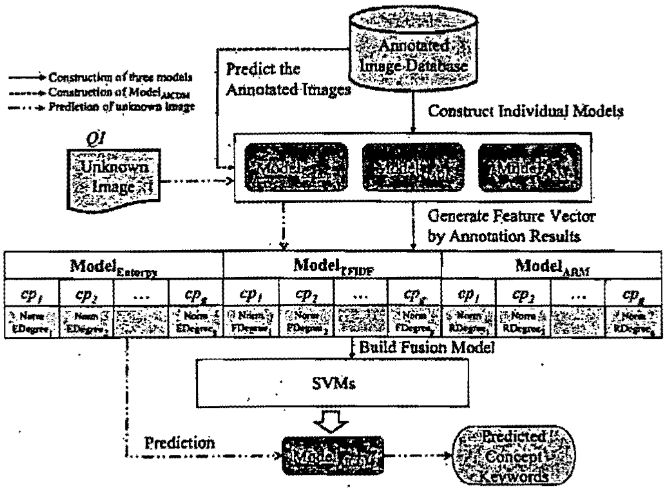


Fig. 5. Procedure of fusing Model$_{entropy}$, Model$_{tf-idf}$, and Model$_{ARM}$.

by the related degrees. The rule-based degree can be defined as (10) at the bottom of the page, where $Lhs(R_i^{QI})$ is the ancestor of R_i^{QI} and $Rhs(R_i^{QI})$ is the descendant of R_i^{QI}, and $Sup(Lhs(R_i^{QI}) \cup Rhs(R_i^{QI}))$ is the support count of itemset "$Lhs(R_i^{QI}) \cup Rhs(R_i^{QI})$". Then, the RDegrees are normalized further. The normalization is defined as

$$NormRDegree_{cp_x} = \frac{RDegree_{cp_x}}{\sum_{i=1}^{y} RDegree_{cp_i}}. \tag{11}$$

For example, there are three longest matching rules:

$$R_1^{QI} : \{C_2, E_5, G_1, D_2\} \rightarrow \{\text{tiger}\},$$
$$R_2^{QI} : \{C_2, E_5, G_1, D_2\} \rightarrow \{\text{grass}\} \text{ and}$$
$$R_3^{QI} : \{C_2, L_3, H_5, D_2\} \rightarrow \{\text{tiger}\}.$$

The related confidence set and the support set are {0.7, 0.35, 0.25} and {10, 20, 8}, respectively. The confidence sets of $sub(R_1^{QI})$, $sub(R_2^{QI})$, and $sub(R_3^{QI})$ are {0.2, 0.4, 0.5, 0.3}, {0.3, 0.2, 0.15, 0.15}, and {0.15, 0.2, 0.1, 0.15}. According to the descriptions mentioned in above sections, the pattern-concept counts, τ_{R_1}, τ_{R_2}, and τ_{R_3}, can be calculated as 2, 2, and 1, respectively. Then, we calculate the RDegree for each concept keyword. For concept keyword "tiger", the related RDegree is (1/2)*10*(0.7 + 0.2 + 0.4 + 0.5 + 0.3) + (1/1)*8*(0.25 + 0.15 + 0.2 + 0.1 + 0.15) = 17.3. For concept keyword "grass", the related RDegree is (1/2)*20*(0.35 + 0.3 + 0.2 + 0.15 + 0.15) = 11.5.

4) Prediction by Fusion Model $Model_{AICDM}$: To achieve better annotation quality, we approximate a near-optimal fusion model. Fig. 5 reveals the procedure of constructing Model$_{AICDM}$. The annotated images are first used as the learning set to construct Model$_{entropy}$, Model$_{tf-idf}$, and Model$_{ARM}$. Meanwhile, the annotation results of the annotated images are generated by the three above models, respectively. Eventually, the derived annotation results and related concept degrees are used as feature vectors to build the fusion model, Model$_{AICDM}$, by utilizing SVM [2]. For each concept keyword, we build a SVM, with respect to radial basis function (RBF) kernel function, to perform the binary classification. The number of dimensions for each model is the number of keyword categories, and total number of dimensions for SVM is triple the number of keyword categories. The whole procedure shown in Fig. 5 starts with an unknown image QI submitted to our proposed annotator. The related EDegree, FDegree, and Rdegree for each concept keyword are derived by the individual prediction models first. Then, the EDegrees, FDegrees, and RDegrees regarded as the feature vectors of the unknown image QI are sent to the SVMs in Model$_{AICDM}$. Thereupon the classification confidence of each concept keyword is derived. At last, the concept keywords are ranked by the related classification confidences.

IV. Empirical Evaluations

A. Experimental Data and Parameter Settings

To make the experiments complete, the experimental data came from the collections of WebImage, PascalVOC07 (Pascal Visual Object Classes Challenge 2007) [3], and ESP [1]. For WebImage, the experimental data is a collection of ten categories gathered from Google, including Bear, Cat, Dog, Lion, Tiger, Flower, Grass, Sky, Snow, and Water. Each category contains 100 unique web images occurring in 100 different web pages. On average, an image contains 1.574 caption terms in this dataset. We select 50% of experimental data as the training set and the others are adopted to serve the testing experiments. For PascalVOC07, it contains 9963 images. We adopt 5011 images as the training set and 4952 images are adopted as the testing set. There are 20 unique concepts in this dataset and an image, on average, contains 1.71 caption terms. For ESP, the set we obtained contains 67 769 images. However, we removed the images with infrequent annotations and then split the set into a training set and a testing set according to [8]. Finally, there are 269 concepts left in this set. The training set contains 18 689 images and the testing set contains 2081 images. Overall there are 269 unique caption terms and the average of caption terms for an image is 4.7. To investigate the effectiveness of our proposed models, three measures, namely precision, recall, and F_1-measure, are used in the experiments. Note that the definitions of precision and recall [16] here are different from that in PascalVOC07 [3]. In this work, the number of the clusters is approximated for each

$$RDegree_{cp_x} = \sum_{R_i^{QI} \in LRS(RQI)} \left[\frac{1}{\tau_{R_i}} \times Sup\left(Lhs\left(R_i^{QI}\right) \cup Rhs\left(R_i^{QI}\right)\right) \times \sum_{R_j \in \left(sub\left(R_i^{QI}\right) \cup R_i^{QI}\right)} Confidence(R_j) \right] \tag{10}$$

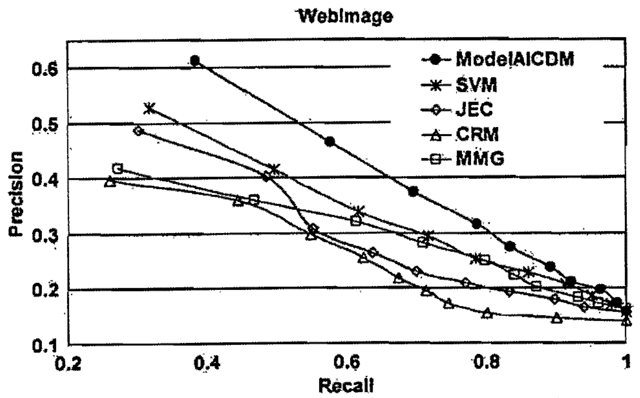


Fig. 6. Precision-recall curves of the proposed and other annotators on WebImage.

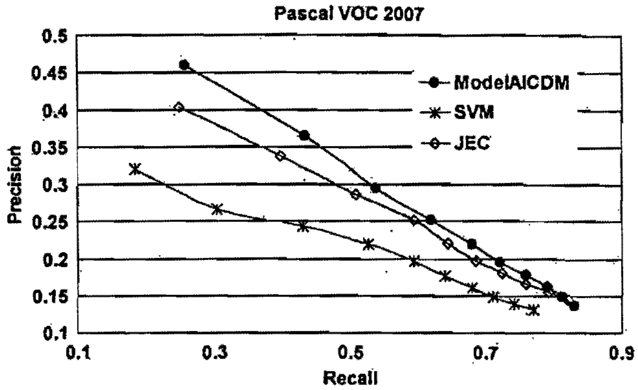


Fig. 7. Precision-recall curves of the proposed and other annotators on PascalVOC07.

dataset and each model by golden search algorithm. Additionally, in the experiments, the numbers of the most-relevant clusters of $\text{Model}_{\text{entropy}}$, $\text{Model}_{\text{tf-idf}}$, and $\text{Model}_{\text{ARM}}$ are 2, 2, and 1, respectively, for all datasets. The experiments were carried out under hardware environment of Intel(R) Xeon(R) E3113 CPU 3.00 GHz, 4 GB memory with Windows Server 2003 R2 SP2 operating system.

B. Experimental Results

The main experiments we explore are the comparisons between our proposed AICDM and other well-known annotators, including CRM [6], SVM [4], MMG [11], and JEC [8], in terms of precision, recall, and execution time. We made our best effort to implement those algorithms based on their papers and got similar performance if their datasets are available. Basically, CRM and MMG are probabilistic-based approaches using image segmentation. Without image segmentation, SVM is classification-based approach and JEC is KNN-based approach. In this experiment, the area under curve (AUC) is the additional measure.

Fig. 6 reveals some interesting results to discuss in detail. First, SVM performs better than CRM, MMG, and JEC for WebImage dataset, and the related AUCs are 0.3934, 0.2925, 0.3321, and 0.3498, respectively. Second, JEC is better than MMG, and MMG is better than CRM. It says that the segmentation-based annotation models are not really better than the models without segmentation. Third, our proposed $\text{Model}_{\text{AICDM}}$ is the best one, and the related AUC is 0.4706. It tells us the truth that the special genes in images can be identified effectively to imply the visual-concept associations. Fig. 7 reveals that the precision-recall curves on PascalVOC07 dataset. In this dataset, CRM and MMG fail to execute because the required memory size is out of the resource. From the remaining three approaches, we can observe that SVM ($\text{AUC} = 0.1912$) does not work well in this dataset due to the higher diversities of images and concepts. In contrast, JEC ($\text{AUC} = 0.2571$) can still keep the good performance through KNN strategy. Compared with above methods, our proposed $\text{Model}_{\text{AICDM}}$ ($\text{AUC} = 0.2892$) can achieve the highest effectiveness for this dataset.

Fig. 8 reveals the comparisons among different approaches on ESP dataset. In this dataset, CRM and MMG also fail to execute because the required memory is out of the resource. In addition, the training cost of SVM is too large, exceeding one month, probably caused by a large number of outliner image features and keywords. Therefore, we only compare $\text{Model}_{\text{AICDM}}$ with JEC. In this experiment, the AUCs of $\text{Model}_{\text{AICDM}}$ and JEC are 0.1512 and 0.1440, respectively. In detail, JEC performs slightly better as the recall is larger than 0.28. However, on average, our proposed $\text{Model}_{\text{AICDM}}$ is much better than JEC in terms of AUC. For each dataset, $\text{Model}_{\text{AICDM}}$ outperforms other well-known annotation approaches in terms of precision, recall, and AUC. That is, from the viewpoint of dataset sensitivity, SVM is highly sensitive to the dataset distribution. In contrast, JEC is more stable than SVM. From all experimental results, we can observe that our proposed $\text{Model}_{\text{AICDM}}$ is insensitive for different datasets.

In addition to the effectiveness, another issue is how efficient the proposed model is by comparing with other annotators. Table II depicts the execution time of each annotator for predicting an image, and there are some observations to discuss.

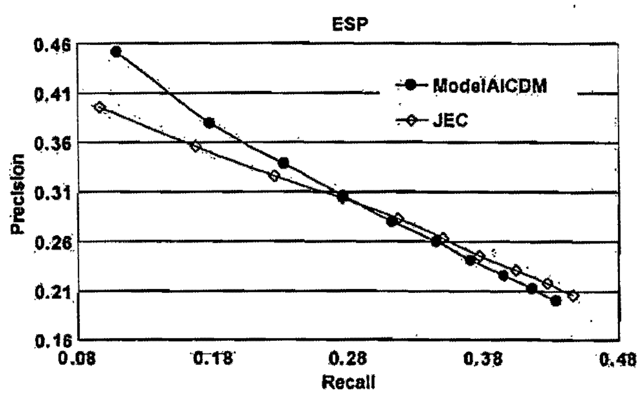


Fig. 8. Precision-recall curves of the proposed and other annotators on ESP.

TABLE II
PERFORMANCE AMONG COMPARED METHODS

Dataset / Method	WebImage	PascalVOC07	ESP
AICDM	0.059 sec.	0.421 sec.	0.632 sec.
CRM	0.112 sec.	*out of memory*	*out of memory*
MMG	0.153 sec.	*out of memory*	*out of memory*
SVM	0.031 sec.	0.109 sec.	*out of training time*
JEC	0.076 sec.	0.477 sec.	4.8495 sec.

First, it shows that our approach, AICDM, is very efficient for generating real-time annotation results. Second, JEC is efficient for small dataset. However, the execution time increases explosively as the training data size increases. For ESP dataset, JEC needs about 4.85 s such that it is not suitable for real applications. Third, SVM is the most efficient, but it does not provide the adequate annotation accuracy.

V. Conclusion

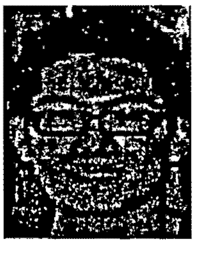
Indeed, an optimal solution to achieve high accuracy annotator is very difficult. This paper constitutes a novel approach to discover the visual-to-concept associations from the image-to-concept distribution. The experimental results show that our proposed annotation approach is effective and efficient in facing data consisting of the diverse relations between visual features and human concepts. On one hand, entropy and tf reflect the local weights of patterns. On the other hand, idf and association rules reflect the global weights of patterns. By making use of both the global and local weights, the fusion model can successfully achieve high annotation quality. In the future, there remain some issues for further investigation. First, we shall explore more visual features to enhance the annotation quality. Second, the spatial information will be a further consideration to enhance our proposed method. Third, we shall further investigate the better fusion methods to reach higher annotation quality. Furthermore, in the future, we shall also explore the proposed algorithms to domains other than multimedia.

References

[1] L. von Ahn and L. Dabbish, "Labeling images with a computer game," in *Proc. SIGCHI Conf. Human Factors on Computer Systems*, 2004, pp. 319–326.
[2] C.-C. Chang and C.-J. Lin, LIBSVM: A Library for Support Vector Machines, 2001. [Online]. Available: http://www.csie.ntu.edu.tw/~cjlin/libsvm.
[3] M. Everingham, L. V. Gool, C. K. I. Williams, J. Winn, and A. Zisserman, The PASCAL Visual Classes Challenge 2007 (VOC2007) Results, 2009.
[4] H. Feng, R. Shi, and T. S. Chua, "A bootstrapping framework for annotating and retrieving WWW images," in *Proc. 12th Annu. ACM Int. Conf. Multimedia*, 2004, pp. 960–967.
[5] J. Fan, Y. Shen, C. Yang, and N. Zhou, "Structured max-margin learning for inter-related classifier training and multi-label image annotation," *IEEE Trans. Image Process.*, vol. 20, no. 3, pp. 837–854, Mar. 2011.
[6] V. Lavrenko, S. L. Feng, and R. Manmatha, "Statistical models for automatic video annotation and retrieval," in *Proc. IEEE Int. Conf. Acoustics, Speech, and Signal Processing*, 2004, pp. 17–21.
[7] J. Li and J. Z. Wang, "Automatic linguistic indexing of pictures by a statistical modeling approach," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 9, pp. 1075–1088, Sep. 2003.
[8] A. Makadia, V. Pavlovic, and S. Kumar, "Baselines for image annotation," *Int. J. Comput. Vis.*, vol. 90, no. 1, pp. 88–105, 2010.
[9] G. Nasierding, G. Tsoumakas, and A. Z. Kouzani, "Clustering based multi-label classification for image annotation and retrieval," in *Proc. IEEE Int. Conf. Systems, Man, and Cybernetics*, 2009.
[10] L.-D. Nguyen, G.-E. Yap, Y. L., A.-H. Tan, L.-T. Chia, and J.-H. Lim, "A Bayesian approach integrating regional and global features for image semantic learning," in *Proc. 2009 IEEE Int. Conf. Multimedia and Expo*, 2009, pp. 546–549.
[11] J. Y. Pan, H. J. Yang, C. Faloutsos, and P. Duygulu, "Automatic multimedia cross-modal correlation discovery," in *Proc. 10th Int. Conf. Knowledge Discovery and Data Mining*, 2004, pp. 653–658.
[12] J.-H. Su, C.-L. Chou, C.-Y. Lin, and V. S. Tseng, "Effective image semantic annotation by discovering visual-concept associations from image-concept distribution model," in *Proc. 2010 IEEE Int. Conf. Multimedia and Expo*, 2010, pp. 42–47.
[13] J.-H. Su, Y.-T. Huang, H.-H. Yeh, and V. S. Tseng, "Effective content-based video retrieval using pattern indexing and matching techniques," *Expert Syst. Appl.*, vol. 37, no. 7, pp. 5068–5085, 2010.
[14] J. Tang, H. Li, G.-J. Qi, and T.-S. Chu, "Image annotation by graph-based inference with integrated multiple/single instance representations," *IEEE Trans. Multimedia*, vol. 12, no. 2, pp. 131–141, Feb. 2010.
[15] V. S. Tseng, J.-H. Su, J.-H. Huang, and C.-J. Chen, "Integrated mining of visual features, speech features and frequent patterns for semantic video annotation," *IEEE Trans. Multimedia*, vol. 10, no. 1, pp. 260–267, Jan. 2008.
[16] V. S. Tseng, J.-H. Su, B.-W. Wang, and Y.-M. Lin, "Web image annotation by fusing visual features and textual information," in *Proc. 22nd Annu. ACM Symp. Applied Computing*, 2007, pp. 1056–1060.
[17] L. Wu, S. C. H. Hoi, R. Jin, J. Zhu, and N. Yu, "Distance metric learning from uncertain side information with application to automated photo tagging," in *Proc. ACM Int. Conf. Multimedia*, 2009, pp. 135–144.
[18] L. Wu, S. C. H. Hoi, and N. Yu, "Semantics-preserving bag-of-words models for efficient image annotation," in *Proc. 1st ACM Workshop Large-Scale Multimedia Retrieval and Mining in Conjunction With ACM Multimedia*, 2009, pp. 19–26.
[19] L. Wu, X.-S. Hua, N. Yu, W.-Y. Ma, and S. Li, "Flickr distance," in *Proc. ACM Int. Conf. Multimedia*, 2008, pp. 31–40.
[20] R. C. F. Wong and C. H. C. Leung, "Automatic semantic annotation of real-world web images," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 30, no. 11, pp. 1933–1944, Nov. 2008.
[21] L. Wu, M. Li, Z. Li, W.-Y. Ma, and N. Yu, "Visual language modeling for image classification," in *Proc. ACM SIGMM Int. Workshop Multimedia Information Retrieval in Conjunction With ACM Multimedia*, 2007, pp. 115–124.
[22] X. J. Wang, L. Zhang, F. Jing, and W. Y. Ma, "Annosearch: Image auto-annotation by search," in *Proc. 2006 IEEE Computer Society Conf. Computer Vision and Pattern Recognition*, 2006, pp. 1483–1490.
[23] X. J. Wang, L. Zhang, X. Li, and W. Y. Ma, "Annotating images by mining image search results," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 30, no. 11, pp. 1919–1932, Nov. 2008.
[24] C. Yang, M. Dong, and J. Hua, "Region-based image annotation using asymmetrical support vector machine-based multiple instance learning," in *Proc. 2006 IEEE Computer Society Conf. Computer Vision and Pattern Recognition*, 2006, pp. 2057–2063.
[25] H.-J. Zeng, Q.-C. He, Z. Chen, W.-Y. Ma, and J. Ma, "Learning to cluster web search results," in *Proc. 27th Annu. Int. ACM SIGIR Conf. Research and Development in Information Retrieval*, 2004, pp. 210–217.

Ja-Hwung Su received the Ph.D. degree from the Department of Computer Science and Information Engineering at National Cheng Kung University, Tainan, Taiwan, in 2010.

He is a postdoctoral fellow in the Department of Computer Science and Information Engineering in National Cheng Kung University. His research interests include data mining, multimedia mining, web mining, and data warehousing.



Chien-Li Chou received the M.S. degree in the Department of Computer Science and Information Engineering at National Cheng Kung University, Tainan, Taiwan. He is currently pursuing the Ph.D. degree in the Department of Computer Science and Information Engineering at National Chiao Tung University, Hsinchu, Taiwan.

His research interests include data mining and multimedia mining.

Ching-Yung Lin received the B.S. and M.S. degrees from National Taiwan University, Taipei, in 1991 and 1993, respectively, and the Ph.D. from Columbia University, New York, in 2000, all in electrical engineering.

He is a Research Staff Member at IBM T. J. Watson Research Center and the IBM Lead of Social and Cognitive Network Science Academic Research Center, Hawthorne, NY. He was an Affiliate Assistant and Associate Professor in the University of Washington, Seattle, from 2003 to 2009, and is an Adjunct Associate Professor in 2005–2006 and Adjunct Professor since 2010 in Columbia University. His research interest includes network science, multimedia security, and multimedia retrieval. He has been focusing on innovating new research paradigms of utilizing multimodality analysis on the social science domain.

Vincent S. Tseng (M'11) is a Professor in the Department of Computer Science and Information Engineering at National Cheng Kung University (NCKU), Tainan, Taiwan. Before this, he was a postdoctoral research fellow in thw University of California at Berkeley during January 1998 and July 1999. He has also acted as the Director for Institute of Medical Informatics of NCKU since August 2008. He has a wide variety of research interests covering data mining, biomedical informatics, multimedia databases, mobile, and Web technologies. He has published more than 200 research papers in referred journals and international conferences, and has held/filed more than 15 patents in the USA and Taiwan.

Inside Risks

The Growing Harm of Not Teaching Malware

Revisiting the need to educate professionals to defend against malware in its various guises.

AT THE RISK of sounding a byte alarmist, may I call to your attention the extreme threat to our world posed by cyberwar, cyberterrorism, and cybercrime? Cyberattacks are already numerous and intricate, and the unquestionable trend is up. To grasp the likelihood of these threats, consider the similarities between physical and virtual violence. Before attacking the U.S. on Sept. 11, 2001, terrorists rehearsed their assaults on a smaller scale at the World Trace Center and in several more distant venues.

Since that infamous date, paralleling physical attacks, cyberstrikes of increasing severity have been carried out against many targets. A few small nations have been temporarily shut down. These attacks are proofs of concept waiting to be scaled up. I hope cybersecurity is on governments' front burners. We ought not wait to react until a devastating cyber-onslaught is unleashed upon us.

Six years ago I wrote a *Communications* Inside Risks column urging that viruses, worms, and other malware be taught ("Not Teaching Viruses and Worms Is Harmful," Jan. 2005, p. 144). The goal of that column was to involve future generations of computer professionals in the expanding global malware problem and persuade them to help curb it. Six years later, malware is still not being taught. And the problem is now much worse.

Malware Evolution

During the first decade of the 21st century the malware problem has evolved in two significant ways. Gone are the lethal but simplistic payloads, produced by improvised, amateur scripts. Gone also are the idiots savants who cut-and-pasted such scripts. Carders, script kiddies, spammers, identity thieves, and other low-level miscreants will probably and deplorably never be completely gone. Gangs of much better trained programmers have largely replaced the individual crooks and nuisance makers. These gangs ply their trade for or in behalf of political syndicates, organized crime cartels, and government-sanctioned but unacknowledged dark ops. Some nation-states covertly train and support them.

What began as gross mischief evolved into criminal activity. Rather than erasing a hard disk drive, why not steal the data stored on it? Or encrypt the drive and extort a ransom for decrypting it? Or hijack the users' computers? Today's malware is a killer app: obfuscated, often; clumsy, never. A medley of viruses, worms, trojans, and rootkits, it is clever, enigmatic—a sly hybrid. Its bureaucratic components (such as installers and updaters) are examples of automated elegance.

Today's malware is a killer app: obfuscated, often; clumsy, never.

Identity theft, botnetting, and many other forms of trespass and larceny continue. Coupled with negligence by institutions that are supposed to safeguard our privacy, the picture is bleak. Malware launchers seem to be always ahead. And their products are no longer stupid capers but skillful software packages. These are valuable lessons that are not being understood by us, the victims.

Malware perpetrators have clearly mastered these lessons. Trading local pranks for global villainy, the perps are readying their next steps on the international political stage, where cyberspace is a potential war zone in-the-making. Inadequately capable of defending ourselves from being burgled, we are easy targets for evil geniuses plotting fresh hostilities.

We cannot protect ourselves from what we do not know. We must not remain stuck in a weak, purely reactive, defensive mode. New malware should no longer be an unexpected, unpleasant surprise. And we must be embarrassed when anti-malware products cause more problems than they solve. As human beings, we have a duty to make our world a better place. As computer professionals, we must do our fair share to stanch malware and prevent cyberwar.

Dealing with Malware

The malware problem must be dealt with on many fronts, proactively. Ideally, we should anticipate and be prepared for new malware. On the research front, funding agencies should follow DARPA's example. If synthetic genomics—the fabrication of new genetic material—merits $50 million in grants per year, so should exploration of new, novel, innovative malware.

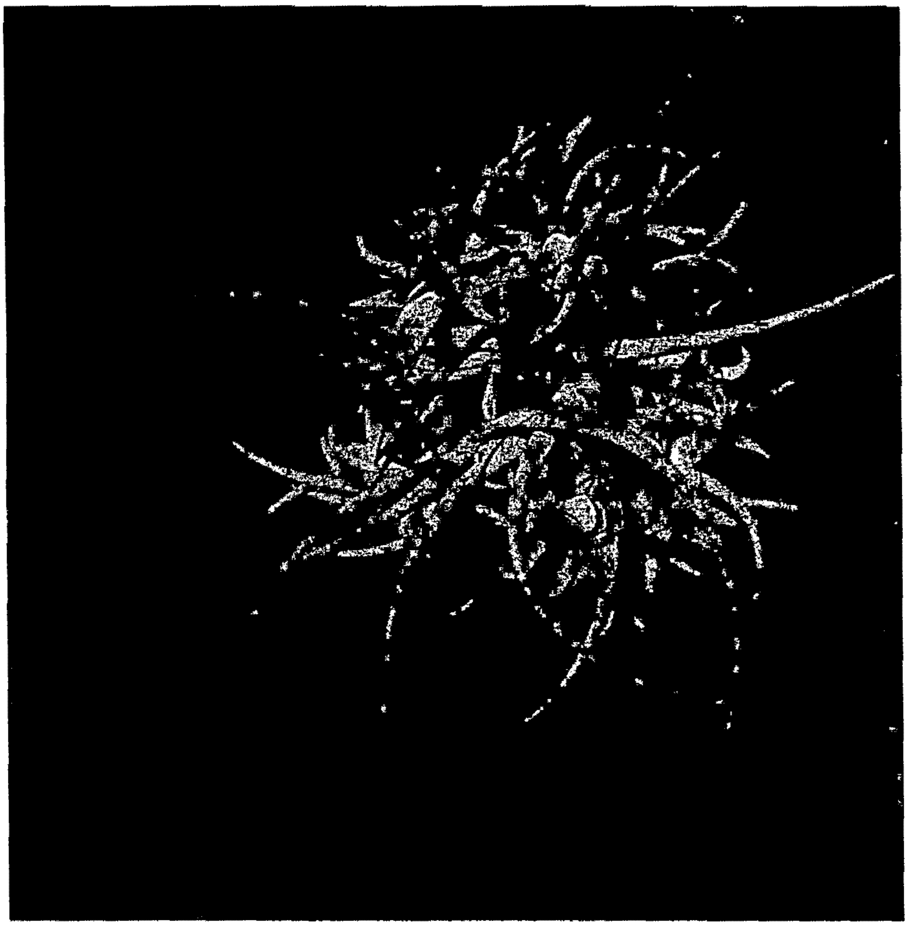
University classrooms and laboratories should serve as locations for spreading malware literacy. Understanding is achieved only by doing. The most effective way to comprehend something is to program it. We cannot afford to continue conferring degrees to computer majors who have never seen the source code of viruses, worms, trojans, or rootkits, never reversed any malware binaries, and never programmed their own malware.

Standard undergraduate computer science curricula offer courses on many disparate topics, such as artificial intelligence and database systems. Students graduating with a degree in computer science are expected to have a solid acquaintance with various subjects that may not be their chosen specialty. Some graduates will dig deeper and become adept at these topics, but the mere fact that these topics are routinely taught to all undergraduate majors is in itself beneficial, because future computer professionals should not be completely ignorant in fields outside their areas of concentration.

Teaching malware will not turn our students into specialists. Malware literacy is not malware expertise. However, unlike artificial intelligence or databases, unfortunately malware is not a standard undergraduate course or even a regular part of an elective computer security course. (Syllabi of computer security courses may pay lip service to diverse issues, including malware, but such courses are overwhelmingly concerned with cryptography.) This means we are matriculating computer scientists whose knowledge of malware is roughly on a par with that of the general population of amateur computer users.

Six years and many articles, interviews, and blogs later, the question, "Should we teach malware?" still evokes apprehension, trepidation, even dread. The answer, of course, is, "Yes, we should." Indeed, we must! It would be irresponsible not to have a single course dedicated exclusively to malware, or a course that studies vulnerabilities in general and malware in particular, or some other combination, so that students completing the course will gain a deeper understanding of malware.

The apprehension, trepidation, and dread will not go away easily. Spreading viruses, worms, Trojans, and rootkits is dirty business. Programming them may feel like doing something forbidden. Over the past six years, I've heard many concerns about the ethics of teaching malware. Taboos are difficult to dispel. For example, the prohibition of dissecting cadavers held back medicine for centuries. How else could aspiring physicians and surgeons learn anatomy? Today, life science majors are not necessarily bacteriologists, parasitologists, or virologists, but all enjoy the benefit of a standard curriculum that offers exposure to microbiology theory and its laboratory practice. This is not the case with computer science majors, whose curricula omit theory and programming of malware. Sadder yet, undergraduates learn sorting, database, and other theories, and carry out their corresponding programming assignments, but do not take a similarly rigorous course on malware.


Visualization derived from disassembled code of MyDoom worm.

Six years ago, when I proposed that not teaching malware was harmful, I was worried that new malware would attain greater sophistication, become much more complex, and that its force and impact would be felt more widely than those of its predecessors. Well, guess what? It has!

The reason we cannot solve the malware problem is simple: We don't have a theory of malware. There are textbooks on sorting and searching, on database methods, on computer graphics. These textbooks present algorithms and source code listings. The many different techniques of sorting, for example, are analyzed and their implementations are examined thoroughly. Students are encouraged to explore new approaches to sorting, to improve on what is known, to push the limits of performance. Whereas such explorations are standard practice in areas such as sorting, they do not exist for malware. Malware was absent from nearly all undergraduate curricula six years ago and it is still absent, for essentially the same technical and ideological reasons.

Technical and Ideological Requirements

On the technical side, teaching malware requires knowing viruses, worms, Trojans, and rootkits, which obligates teachers to have read their source code, which in turn requires them to have the ability to reverse the binaries, and the facility to launch, run, and infect machines on an isolated subnet. Having read a sufficiently large, representative sampling of historic malware source code then leads to formulating various generalizations to build a theory of malware that can be tested by writing derivative malware, new in a shallow sense but not necessarily innovative. These experiences then should culminate in inventing never-before-tried malware to foresee trends in cyberspace.

On the ideological side, arguments range from "moral purity" to "allocation of responsibility." These arguments are fueled by fear of the unknown, especially when the unknown is potentially toxic. Having one's reputation ruined by being labeled irresponsible, negligent, reckless, or incompetent is a strong disincentive. It is difficult to imagine computer scientists losing their professional standing or community esteem by demonstrating new multi-core implementations of Batcher's sort, especially if it beat all current sorting techniques; but it is not difficult to conjure the poisonous politics of unveiling new malware that would escape detection by all current commercial anti-malware products. Raising the stakes with powerful sorting algorithms is a laudable, honorable endeavor; casting a spell with powerful new malware is considered undignified per se.

The reason we cannot solve the malware problem is simple: We don't have a theory of malware.

Detecting and arresting malware and its launchers won't be easy unless we ramp up on all fronts, especially education.

That malware should be taught to computer science majors runs into a frequent and bothersome accusation—that we will be granting diplomas to hordes of malicious hackers, aiding and abetting greater misbehavior than is being suffered already. Physicians, surgeons, nurses, pharmacists, and other health professionals have the know-how with which to inflict pain, torture, and death. Every profession may have its "black sheep," but it is obvious that society benefits by having an absolute majority of responsible and caring professionals.

Conclusion

I began this column by calling your attention to the forthcoming triple trouble of cyberwar, cyberterrorism, and cybercrime. The last of the three—cybercrime—is abundantly in our midst already. The other two menaces are works in progress. All three typically deploy via malware. (Human gullibility is, tragically, a contributing factor.) The preferred way thus far has been to exploit overlay networks or saturation-bomb regions of the Internet to build a broad-based infrastructure of illegally tenanted user machines and servers—a large botnet, responsive to peer-to-peer and command and control communications. Such a botnet's unwitting foot soldiers—your and my machines—are powerful weapons in cyberspace, capable of mounting targeted distributed denial-of-service attacks against individual users, institutions, corporations, and governments. Botnets built by worms can remain silent and undergo quiet maintenance and upkeep between bursts of activity. Botnet battles—territorial disputes and turf fights—are vicious confrontations for supremacy, worth billions of dollars and euros. For nation-states, the cyber-arms-race is on: those with the strongest malware will emerge as super-cyber-powers. None of these near-future developments can be wished away. And we continue to harm ourselves by not teaching malware.

May we let thousands of talented young minds lie fallow until our ignorant denial of the problem can no longer be condoned? How much malware damage should we tolerate? Until universal infection is the status quo? How are we to respond to massive but very likely covert malware pandemics? Would our response be capable of restoring and maintaining stability? More importantly, would we be able to verify the effectiveness of such a response?

Detecting and arresting malware and its launchers won't be easy unless we ramp up on all fronts, especially education. Millions of educated professionals are our best defense. Classrooms can be constructive idea generators. Let's not wait another six years for important ideas, such as malware prevention and preemptive interdiction, to be realized.