1. **译文**

**结合语义和统计信息进行Web敏感文本过滤**

**摘要**

网络敏感信息是指网络上含有色情内容的文本、图片等形式的信息。如何过滤这些有害信息引起了研究人员的兴趣。为了保证网络内容的安全，各国政府也对这一问题的研究给予了极大的支持。本文首先简要回顾了网络敏感信息过滤的最新发展，然后分析了敏感文本的统计特征和语义特征，并用一个类似于CNN的词网来表示。最后，提出了一种语义与统计相结合的网络敏感文本过滤方法。实验结果证明了该方法的有效性。

1. **简介**

互联网为人们获取和交换信息提供了便利。然而，它也给我们带来了有害的内容，如色情、暴力和其他非法信息。这些有害的内容自然会对整个社会产生严重的影响，尤其是年轻人。因此，敏感信息的过滤具有重要的意义，是近年来研究的热点之一。

文献中已经有大量的过滤方法，大致可分为以下三类[1][2]。

1. **PICS** （因特网内容选择平台）本质上是一组用于对web站点进行评级的内容评级系统的规范。通常有两种方法来评价web页面。一种是自我评分，另一种是第三方评分，其区别在于评分结果是否由网络发布者给出。过滤系统可以通过检查网站的评级信息进行操作。
2. **黑名单和白名单**。由预先手动或自动生成网站列表，形成黑名单和白名单。黑名单记录禁止访问的网站的url。白名单记录允许访问的web站点的url。对于给定的新web页面，是否允许访问取决于所请求的URL与黑名单或白名单的匹配结果。
3. **关键字过滤**。这种方法的思想是，敏感文本总是包含一些特定的单词或短语，而它们通常不会出现在正常文本中。由这些特定的词或短语組成的单词列表，通常被用来构建关键字过滤方法，即计算语句中包含的词库匹配单词数，如果一个web页面匹配的单词数超过一个预定义的阈值，则不允许被浏览。

上述方法在敏感信息过滤方面都有各自的优点，但缺点也很明显。由于PICS不是强制性的标签系统，所以评级信息并不总是可用的。很难保持URL列表的完整和最新；因此，黑名单和白名单的方法不能有效地处理敏感页面。在基于关键字的过滤中，很多普通文本在单词列表中也包含一些特定的单词。因此，这种方法将不可避免地导致过度阻塞。

目前有许多商业网络过滤系统可用。2001年，欧盟委员会发起的网络保护项目[3]挑选了50个商业网络过滤系统并对其性能进行了评估。由于这些系统大多使用上述一种或多种传统方法，因此它们显然不能在实际应用中提供令人满意的结果。

为了更准确地过滤web上的敏感信息，近年来，研究人员将重点放在了智能内容识别方面，提出了多种检测成人图像[4]的算法。然而，他们只能在一定程度上识别某些类型的成人图像。其他一些研究人员更关注敏感文本的过滤[1][2]。Lee[1]等人在传统的基于关键字的过滤方法的基础上，通过计算文本中出现的关键字的数量得到一个特征向量，然后将该向量作为输入到KSOM神经网络中进行文本分类。尽管论文的结果表明这种方法是有效的，但当输入的文本是关于性健康和其他相关主题时，通常会给出错误的结果。Du[2]等人使用文本分类来过滤web上的敏感文本。在一个仅从Yahoo的成人类别中收集成人文本的测试数据集上，他们的方法获得了很高的准确性。事实上，情色故事和文本的风格并不相同，所以这种方法在现实世界中并不适用。

综上所述，在这方面还有三个主要问题没有很好地解决，即

**过度屏蔽问题**：如何区分敏感文本与性健康、文化等相关主题文本是一个具有挑战性的问题，许多方法都不能有效地解决它。

**拼写错误问题**：如果特定的单词有意或无意地拼写错误，许多方法可能无法正常工作。

**单词列表问题**：如何构造一个足够实用的单词列表是许多基于关键字的过滤方法的关键问题。然而，到目前为止，还没有人关注这个问题。

在这篇论文中，我们将专门把对敏感信息检测有用的单词分为三类。结合文本的语义和统计信息，得到了一种更有效的文本特征，用于敏感信息的过滤。本文的其余部分组织如下。第2节简要介绍了细胞神经网络(CNN)，分析了敏感文本的语义特征，并在第3节设计了一个类似于CNN的词网进行特征表示。第4节简单总结了该算法的主要步骤。实验结果在第5节给出并讨论，第6节给出最后的结论。

1. **细胞神经网络**

CNN是一个定义在离散n维空间[5]中的大规模并行计算范例，其中每个单元是一个多输入单输出处理器。细胞之间的连接构成了网络。CNN与其他神经网络的主要区别在于，只允许相邻细胞之间的连接，这使得我们可以通过局部交换和处理信息来获得全局的处理。图1显示了cnn的一个示例。

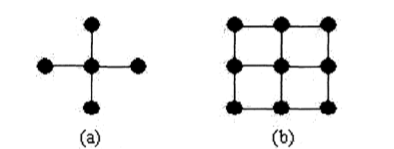


图1 (a) A细胞及其相邻细胞 (b) 3\*3大小的二维CNN

一个CNN动态系统可以在连续时间(CT-CNN)或离散时间(DT-CNN)[5]下工作。CNN中的每个单元格都有一个内部状态变量。细胞的内部状态，它的输出和来自相邻单元格的输出，三个部分，决定了它的最终输出。离散时间情况下的数学描述如下：

1. **敏感文本的特征分析和表示**
2. **算法**
3. **实验评估**
4. **结论**

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**参考文献**

1. P.Y. Lee, S.C. Hui and A. Fong, "Neural Networks for Web Content Filtering", IntelligentSystems, 17(5): 48-57, 2002
2. R. Du, R. Safavi-Naini and W. Susilo, "Web Filtering Using Text Classification", Proc. the 11th IEEE Intl. Conf on Netvork, pp. 325 330, 2003.
3. NetProtect Research Group, "Report in Filtering Techniques and Approaches NETPROTECT: WP2: 2.3 VI.023", TechnicalReport, Oct 2001
4. D. Forsyth and M. Fleck, "Automatic Detection of Human Nudes", InternationalJournalofComputer Vision, 32 (1): 63-77, 1999.
5. <http://www.ce.unipr.it/pardis/CNN/#InterPoint>
6. A. Lukianiuk, "Capacity of Cellular Neural Networks as Associative Memories ", Proc. the Fourth IEEE Int. Workshop on Cellular Neural NetworksandTheirApplications, pp. 3740, 1996.
7. M. G. Milanova, A. C. Campilho, and M. V. Correia, "Cellular Neural Networks for Segmentation of Image Sequence", Proc. the 11th Portuguese Conference on Pattern Recognition, pp. 49-54, 2000.
8. K. Aas and L. Eikvil, "Text Categorization: a Survey", TechnicalReport -941, Norwegian ComputingCenter, 1999.
9. T. Joachims, "Text Categorization with SupportVectorMachines: Learningwith Many Relevant Features", Proc. the 10th European Conference on Machine Learning, pp.137-142, 1998.
10. http://www sie.ntu.edu.tw/-cjlin/papers/guide/guide.pdf
11. **原文**

**Web Sensitive Text Filtering by Combing Semantics and Statistics**

**Abstract**

Web sensitive information is defined as texts, pictures and other forms of information which contain erotic content on web. How to filter this harmful information attracts researchers' interests. In order to keep web content safe, governments have also given great support on the research on this problem. This paper first briefly review recent developments in web sensitive information filtering then the statistic and semantic features of sensitive texts are analyzed and represented by a CNN-like word net. Finally a novel method which combines semantics and statistics is proposed to filter sensitive text on web. Experimental results have demonstrated the proposed method's promising performance.

**I. Introduction**

Internet has facilitated ones to obtain and exchange information. However, it also brings us harmful contents such as pornography, violence and other illegal messages. These harmful contents naturally have serious influence on the whole society, especially young people. So sensitive information filtering is ofgreat importance, and has been one ofmost active researchtopics recently.

There have been a large number offiltering methods in the literature, which can be roughly classified into three major classes as follows [1][2].

PICS (Platform for Internet Content Selection) is in essence a set ofspecifications for content-rating systems that can rate web sites. There are usually two measures to rate the web pages. One is Self-rating and the other is the Third-part rating, which are distinguished by whether the rating results are given by web publishers or not. The filtering systems can operate through checking this rating information ofweb sites. Blacklists and Whitelists.

Blacklists and Whitelists are lists ofweb sites which compiled manually or automatically beforehand. Blacklists record URLs of web sites which are forbidden to access. Whitelists record URLs of web sites which are allowed to access. For a given a new web page, whether it is allowed to access or not depends on the matching result ofthe requested URL with the Blacklists or Whitelists.

Keyword-based Filtering. The idea of this approach is that sensitive texts always contain some specific words or phrases while they do not usually appear in normal texts. A word list that is composed ofthese specific words or phrases is usually needed to be constructed for keyword-based filtering methods, which count he number ofwords contained in the wordlist by matching the word list and a web page and do not allowed to browse when the number exceeds a predefined threshold.

Each kind ofmethod mentioned above does have its own advantages in sensitive information filtering, but their drawbacks are also obvious. The PICS is not a compulsory labeling system, so the rating information is not always available. It is very difficult to keep the URL lists complete and up to date; the approach ofBlacklists and Whitelists thus cannot deal with the sensitive pages effectively. As to the Keyword-based Filtering, many normal texts also contain some specific words in the word list. Therefore, this approach will leadto overblocking inevitably.

There are many commercial Web-filtering systems available currently. In 2001, The NetProtect project [3] launched by European Commission selected fifty commercial web-filtering systems and evaluated their performance. Because most of these systems use one or more traditional approaches above, it is clear that they cannot provide satisfactory results in real applications.

In order to filter the sensitive information on web more accurately, researchers have recently focused on research on the intelligent content recognition. Various algorithms are proposed to detect adult images [4]. However, they can only recognize certain kinds ofadult images to some extent. Some other researchers have paid more attention to sensitive text filtering [1][2]. Based on the traditional approach of Keyword-based Filtering, Lee et al. [1] counted the number ofkey words appearing in the text to obtain a feature vector, and then used the vector as the input into a KSOM neural network for text classification. Although the results in the paperhave shownthatthis method is efficient, itusually gives wrong results when the input text is about sexual healthy and other related topics. Du et al. [2] used text classification to filter sensitive texts on web. On a test data set in which adult texts were collected only from the adult category of Yahoo, their method achieved a high accuracy. In fact, the styles of erotic stories and texts are not in common, so this approach cannotworkwell inthe real world.

In summary, there are three major problems which are not well solved in this area, i.e.

Overblocking problem: How to distinguish sensitive texts from related topic texts such as sex-related health and culture is a challenging problem which many methods can not solve efficiently.

Mis-spelled problem: Many approaches probably cannot work normally if the specific words are misspelled intentionally orunintentionally.

Wordlist problem: How to construct a sufficient and practical wordlist is a key problem for many keyword-based filtering approaches. However, so far, nobody has focused on this problem.

In this paper, we will specifically divide words which are useful for sensitive information detection into three classes. By combining semantics and statistics of texts, a more efficient text feature is obtained for the purpose of sensitive information filtering. The remainder ofthis paper is organized as follows. Section 2 briefly introduces the Cellular Neural Network (CNN), and semantic features of sensitive texts are analyzed and a CNN-like word net is designed for feature representation in Section 3. Section 4 simply summaries major steps of the proposed algorithm. Experimental results are given and discussed in Section 5, prior to conclusions in Section 6.

**II. Cellular Neural Network**

CNN is a massive parallel computing paradigms defined in discrete N-dimensional spaces [5], in which each cell is a multiple input-single output processor. Cells and connections among them form the network. The main difference between the CNN and other neural networks is that connections are only allowed between adjacent cells, which allows obtaining global processing by exchanging and processing information in a local manner. Figure 1 shows an example ofCNN.

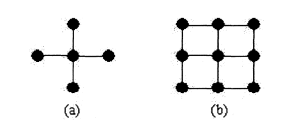


Fig.1. (a) A cell and its adjacent cells and (b) a two-dimensional CNN of 3\*3 size.

A CNN dynamical system can operate in continuous (CTCNN) or discrete time (DT-CNN) [5]. Each cell in a CNN is characterized by an internal state variable. Three parts, namely its internal state, its output and outputs from its adjacent cells, decide its final output. A mathematical description in a discrete time case is as follows:



where x(t) is the internal state of a cell in time t. y(t) is the output. u(t) is external input from adjacent cells and I(t) is a local value called bias. In addition, Jf and f2 are twoparametric functions respectively.

The theory ofthe CNN has been widely applied in many areas such as signal and image processing [6][7]. In this study, we will use the main idea ofthe CNN to construct a CNN-like word net to illustrate semantic features ofthe inputtexts.

**III. Feature Analysis And Representation For Sensitive Text**

1. Statistic feature analysis

Text categorization is to assign a new text into the predefined categories. The first and also predominate step is to transform texts into a suitable feature representation. There are many methods to define text feature. The common method is using statistical data of words appearing in text. Vector Space Model (VSM) may be the most notable model in text categorization, in which [8], documents are generally represented by vector ofwords. Let A denote the feature ofa text,

A = (al, a2. . . ai, an ) (2)

where ai is the weight of word i and N is the number of words we will count. The key step here is how to define the words' weights. Kerstin et al. [8] described 6 different weighting strategies in their paper. Let fJ be the frequency of word i in the text. A simple approach is to use the frequency ofword as its associated weight, i.e.

ai = fi (3)

The task of sensitive text filtering is to determine an input text sensitive or normal, it may be considered as a text categorization problem. Most of the existing texts filtering approaches are based on this idea, in which a wordlist which contains some specific words is firstly compiled. Then a vector like (2) is created to the text. Obviously, such vector is the statistical feature ofa text. Although it is useful to classify the text, almost all ofthe semantic information about the text is notyet explored ifonly usingthis statistical method.

1. Semanticfeature analysis

Generally, some specific words such as sex and breast are considered as the semantic features ofa sensitive text. In fact, many sex-related but normal texts also contain these words. So they may provide error clues to predict the category of a text. In addition, if the Miss-spelled problem occurs, any clues from the text will impossibly be collected correctly. So howto extract right clues from a text willbe critical.

Words in sensitive texts may give different semantics from they give in normal texts. But we don't know whether the input text is sensitive or not in the beginning. Other information such as context ofwords will be needed to decide whether we should extract these words as clues or not. As we know, some words do not contain any sensitive semantics by themselves. But ifthey are combined with some other words, they can provide sensitive clues. Based on the above consideration, here we specifically divide words which useful for us to filter into three classes according to semantics as follows:

**Obvious Keywords**: This class ofwords approximately only appears in sensitive texts. In a statistical sense, the probabilities oftheir appearances in normal texts are close to zero. In a semantic sense, they represent erotic meaning.

**Hidden Keywords**: This class of words does not contain erotic meanings. But for some reasons, there are confused relations between them and sensitive texts. That is to say, the probabilities they appear in sensitive texts are high though they also appear in normal texts.

**Logical Keywords**: This class of keywords can be further divided into two subclasses. One is multi-semantic word such as breast, which provides normal information in normal texts and erotic information in sensitive texts. The other is that ifonly some specific words are companied with them, these words are considered as erotic keywords.

Many existing approaches only use obvious keywords and the first subclass of logical keywords. In fact, hidden keywords and the second subclass of logical keywords also can greatlyhelp classify anew text.

There are giant numbers ofwords in human brains and they are not isolated each other. These words form a huge net by semantic relations among them, which will facilitate to process text information accurately. For example, when we read a word in an article, we may associate with other semantic related words. In addition, when we read a word, the node corresponding to this word accepts it as an input. Then the node's state is changed according to its previous state and the states ofits adjacent nodes. This mechanism enlightens us that the three classes ofkeywords and their semantic relations can represent the semantic features of the sensitive texts reasonably. In the next subsection, we explain the semantic information among them and accordingly construct a CNNlike word net to describe the semantic features. Figure 2 shows the main difference in keyword set or wordlist between the traditional and our approaches.

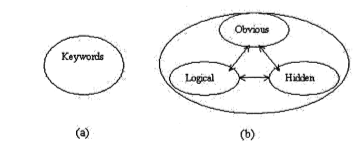


Fig.2. Traditional keyword setand ourkeyword set.

1. CNN-likewordnet

There exists semantic information among words. When we see the word "teacher", the word "student" may appear in our minds unconsciously. Provided that you only see three words "parents", "study" and "children" in aparagraph, you may say this paragraph is about parents' role in children's education. It means that only several separated words can give us an integrative meaning. When you see a word "students", you may be not sure whether it means middle school students or university students. But, if you see "bachelor" in the following paragraph, you can say it most possibly means university students. Examples like these have shown that semantic information among words can help obtain more informative clues about words. In this study, we will try to explore this information to help us extract right clues from a text.

To construct a CNN-like word net, we define a cell as a word. And four parameters are used to describe a cell. They are state, position set for appearances, number and activated numberrespectively. A cell hasthree kinds ofstates: sleep ifit doesn't appear, fallow ifithas appeared but not been activated and activity if it is activated. The output of a cell is equal to the internal state and the internal state ofa cell is described by the four parameters above. Instead ofusing strict function to describe the input and output of a cell, we just use some semantic rules. A cell and its adjacent cells are shown in Figure 3.

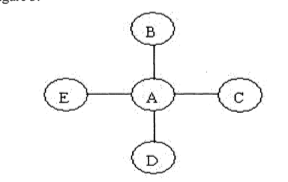


Fig.3. A word cell and its adjacent cells.

Provided that A is a hidden keyword and its initial state is sleep. When there is an input forA, ifthe parameters ofB, C, D and E and previous parameters ofA meet a certain rule, then A will be activated. Otherwise the node A turns to the fallow state. This process can help us extract sensitive-prone words efficiently. For example, in a text about sex healthy, although A may also appear, but the parameters can't meet a certain rule, thenA can'tbe activated. Ifthere is aword similar toA, andthe parameters meet the rule, we can also activate A. Onlythose activatedwords are considered as useful clues. IfA is an obvious or logical keyword, the disposal is similarto this. It is obvious that this process can help solve the Miss-spelled problem. Because when we see a miss-spelled word, we can return to its context or other semantic information to understand itcorrectly.

The whole CNN-like word net is constructed by a number of paradigms described above. Link between any two cells shows their semantic relations. Rules indicate in what case a cell can be activated. Differentparadigms have different rules. Links and rules among the three kinds of words can effectively representthe semantic features ofsensitive texts.

**IV. The Algorithm**

The key step ofthe proposed approach is constructing the CNN-like wordnetproperly. Keywords are selected according to our keyword classification strategy. Ideally, we had better use machine-learning to automatically attain rules (semantic relations) among cells (words). Considering that only specific texts needto be filtered, here we construct the CNN-like word netmanually.

1. Feature extraction

The initial states of all cells are set to sleep. Major steps involved in feature extraction are summarized as follows.

**S1.** Obtain a word from the input text and match the word with each cell inthe CNN-like netgradually. Find a cell which has the highest similarity with the input word. Ifthe similarity score exceeds a predefined threshold, adjust the parameters except the state and activated number of this cell, and then turnto S2; else, turn to SI.

**S2.** Get the parameters of the cell and its adjacent cells fromthe CNN-like net. Ifthese parameters meet a certain rule, then this cell is activated. Its activated number is added to one and its state turns to activity. Otherwise, itturns to fallow.

**S3.** Ifits state is changed, adjust states ofthe adjacent cells by the same process as S2. Then adjust the whole net iteratively. Ifallwords ofthe texthave been processed, turn to S4; else turn to 51.

**S4.** Collect the activated number of each cell and forms a vector.

The vector is used to represent semantic and statistic features ofthe inputtext.

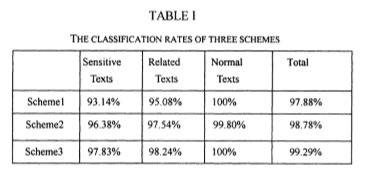
1. Trainingandclass.ification

Support vector machine (SVM) is a very popular classification technique now. It transforms classification to a lineal layout problem. The algorithm finds a hyper plane between different classes ofthe training data. Once the hyper plane is determined, we can use it to classify a new data [2]. SVM is also applied in text classification [9]. We choose SVM as our classifier for its well performance in text classification.

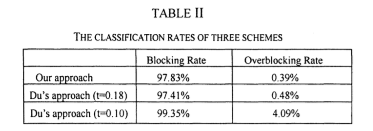
**V. Experiment**

To evaluate the proposed method's performance, 3162 Chinese texts have been collected from Internet, which include 577 sensitive texts, 585 sex-related but normal texts and 2000 normal texts. The normal texts consist of 10 subcategories, namely Arts, Business, Science, Computer, News, Shopping, Game & Recreation, Society, Health and Sports. Each subcategory contains 200 web texts. The Health subcategory was mainly collected from the following web sites: www.xyxy.net, health.21cn.com, www.finl2O.com and www.medicch- ina.com. Compared to other text databases for web filtering, only we collected sex-related normal samples such as sexualhealth, sexualculture and sexual education. 300 sensitive texts, 300 sex-related normal texts and 1000 normal texts are used as training data, andthe remaining serves as test data. A list of 109 indicative terms comprising 29 obvious keywords, 33 hidden keywords and 47 logical keywords has been compiled. Some simple rules are constructed to describe the relationships among these three kinds of keywords. All keywords and simple rules form the CNN-like word net.

Three different feature extraction schemes are designed to test the effectiveness of our approach. The first is the traditional scheme, in which only the number ofeach obvious keyword and a part of logical keywords is counted. The second is to count all ofthe three kinds ofkeywords. The third is to count keywords through the CNN-like word net. The free software Libsvm-2.6 [10] is used to train and predict on our database. The experimental results are summarized in Table 1, from which and false recognized texts, we can get several useful conclusions: (1) Comparing scheme 1 with scheme 2, we see that our definition three kinds of keywords and constructing the keyword set according to this definition can improve the recognition rates noticeably. But because the keyword set contains many logical keywords and hidden keywords, it is inevitable to classify some normal texts into sensitive category. (2) Using the CNN-like word net to extract features oftexts, we get the best classification rates. It proves that CNN-like word net can represent the semantic feature of sensitive texts properly. (3) The real sensitive texts have protean styles and contents. So in order to get a higher classification rate, we need to enlarge the keyword set. (4) Because we only consider some naive semantic relations among words, some normal related texts are also predicted as sensitive texts.



Du et al. [2] applied text category to filter sensitive web pages. Although their training and test sets are English texts and ours are Chinese, we make comparison between their approach and ours. Because both their and our methods are not specific language-oriented. In their approach, it needs to set the threshold t manually. Table 2 shows the results ofthe two approaches, where Blocking Rate is the fraction of the correct classified texts in the sensitive text set, while Overblocking Rate is the fraction ofthe false classified texts in the non-sensitive text set. The results of Du's method are taken directly from his paper. It can be seen that our result is better than theirs in an overall manner, even though our text data set is more challenging than theirs. They collected test data about adult only from the adult category of Yahoo and didn't contain sex-related normal texts.



Experimental results also show that that our approach can solve the Overblocking problem and Wordlist problem efficiently.Our classification ofkeywords can guide us how to select keywords to construct wordlist (or keyword set) more efficiently. Our CNN-like word net can help extract right clues from text and avoid blocking normal texts. We have not yet done experiments about the Mss-spelled problem. To English words, it is easy to calculate the similarity between two similar words. For example, the words 'University' may be spelled as 'Uinervtisy'. But it is relatively more difficult to handle the Chinese words because they may be similar in pronunciation or shape. But it is believable that, ifthere is a simple method to calculate the similarity between the Chinese words, the proposed approach can solve the Miss-spelled problem.

**VI. Conclusions**

This paper have defined three kinds of keywords and constructed a CNN-like word net to extract and represent semantic and statistic features of texts. This study is an attempt to use semantics to solve the three unsolved problems in this area. Experimental results have shown that the proposed approach is very promising. Future work will focus on (I) Enlarging our keyword set and designing more accurate semantic rules among words so as to construct a better CNN-like word net and (2) Finding a feasible way to calculatethe similaritybetweentwo Chinese words.

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**References**

1. P.Y. Lee, S.C. Hui and A. Fong, "Neural Networks for Web Content Filtering", IntelligentSystems, 17(5): 48-57, 2002
2. R. Du, R. Safavi-Naini and W. Susilo, "Web Filtering Using Text Classification", Proc. the 11th IEEE Intl. Conf on Netvork, pp. 325 330, 2003.
3. NetProtect Research Group, "Report in Filtering Techniques and Approaches NETPROTECT: WP2: 2.3 VI.023", TechnicalReport, Oct 2001
4. D. Forsyth and M. Fleck, "Automatic Detection of Human Nudes", InternationalJournalofComputer Vision, 32 (1): 63-77, 1999.
5. <http://www.ce.unipr.it/pardis/CNN/#InterPoint>
6. A. Lukianiuk, "Capacity of Cellular Neural Networks as Associative Memories ", Proc. the Fourth IEEE Int. Workshop on Cellular Neural NetworksandTheirApplications, pp. 3740, 1996.
7. M. G. Milanova, A. C. Campilho, and M. V. Correia, "Cellular Neural Networks for Segmentation of Image Sequence", Proc. the 11th Portuguese Conference on Pattern Recognition, pp. 49-54, 2000.
8. K. Aas and L. Eikvil, "Text Categorization: a Survey", TechnicalReport -941, Norwegian ComputingCenter, 1999.
9. T. Joachims, "Text Categorization with SupportVectorMachines: Learningwith Many Relevant Features", Proc. the 10th European Conference on Machine Learning, pp.137-142, 1998.
10. http://www sie.ntu.edu.tw/-cjlin/papers/guide/guide.pdf