Text Retrieval from Document Images based on N-Gram Algorithm

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Abstract

In this paper, we propose a method of text retrieval from document images using a similarity measure based on an N-Gram algorithm. We directly extract image features instead of using optical character recognition. Character image objects are extracted from document images based on connected components first and then an unsupervised classifier is used to classify these objects. All objects are encoded according to one unified class set and each document image is represented by one stream of object codes. Next, we retrieve N-Gram slices from these streams and build document vectors. Lastly, we obtain the pair-wise similarity of document images by means of the scalar product of the document vectors. Four copora of news articles were used to test the validity of our method. During the test, the similarity of document images using this method was compared with the result of ASCII version of those documents based on the N-Gram algorithm for text documents.

Keywords: Document Image, Information Retrieval, Similarity Measure, N-Gram Algorithm

1. Introduction

The Singapore National Library archives the entire set of past issues of major newspapers in Singapore. All issues of the newspaper are in microfilms carefully preserved in the National Library [1]. Many researchers have frequented the microfilm section of the Singapore National Library with a wide variety of interests. It is thus proposed that the microfilm images be digitized to facilitate retrieval of relevant news articles based on text similarity.

There are many ways to measure text similarity of documents. One way is to analyze the similarity of the documents' contents based on semantics but this needs a large amount of processing time and is dependent on the specific language used. Another way is to use a statistical method to gauge the text similarity directly without the need to understand the meaning of documents. A common statistical method is N-Gram algorithm. This method is easy to implement without too much processing time. Many researchers have used it to classify document texts.

There are two methods to retrieve information from document images. One is the retrieval based on optical character recognition (OCR) followed by the usual text retrieval techniques. However, OCR systems are not perfect and they require significantly more processing time than gauging similarity. Another approach is the retrieval based on the image content. This does not require language identification. This paper adopts the latter approach by gauging the similarity of document images using an N-Gram algorithm without the recognition of the characters.

The remainder of this paper is organized as follows. Section 2 surveys related works in text retrieval of electronic texts as well as document images. Section 3 describes the feature extraction process to detect and classify character objects from the document images. Section 4 presents the N-Gram algorithm that measures the text similarity based on the character objects extracted. Section 5 discusses experimental results that confirm the validity of the proposed model. Finally, conclusions and future work are given in Section 6.

2. Related Works

Over the past few decades, methods of categorisation and retrieval of machine-readable texts [2-4] had been proposed. They have relied on self-evident utility of words, sentences, and paragraphs for sorting, categorising, and retrieving texts. Furthermore, various means of suppressing uninformative words, removing prefixes, suffixes, and endings, interpreting inflected forms, etc. have been developed. Depending on the application, these methods share a number of potential drawbacks: they require a linguist or a polyglot for initial set-up and subsequent tuning, they are vulnerable to variant spellings, misspellings, and random character errors, and they tend to be both language-specific and domain-specific.

The purely statistical characterisation of text in terms of its constituent N-Grams (sequences of N consecutive characters) [5] has been applied to text analysis and document processing, including spelling and error correction [6-12], text compression [13], language identification [14-15], and text search and retrieval [16-17]. Basing on this statistical characterisation, M. Damashek [18] has proposed a simple but novel vector-space technique that makes sorting, clustering and retrieval feasible in a large multilingual collection of documents.

Damashek's method does not rely on words to achieve its goal, and no prior information about the document content or language is required. It only collects the frequency of each N-Gram to build a vector for each document and the processes of sorting, clustering and retrieval can be implemented by measuring the similarity of the document vectors. It is language-independent. A little random error only influences a small quantity of N-Grams and will not change the total result. This method thus provides a high degreee of robustness.

Text in document images is a more complicated matter for text retrieval. One common method is to convert it to machine readable text using optical character recognition (OCR) first and then use the usual text retrieval techniques. However, character recognition systems are not perfect and they require a significant amount of processing time. Furthermore, OCR is language-dependent. A typical system can only recognize one or several languages. We need to know the specific language in the document beforehand.

Another approach is to retrieve information based on the image content directly. This does not require language identification. Recently, several researchers have made such an attempt in a number of applications. For example, F. R. Chen and D. S. Bloomberg [19-20] have described a method for automatically selecting sentences for creating a summary from a document image without recognition of the characters in each word. They build word equivalence classes by using a rank blur hit-miss transform to compare word images and use a statistical classifier to determine the likelihood of each sentence being a summary sentence. Hull and Cullen [21] have proposed a method to detect equivalent document images by matching the pass codes of document. They create a feature vector that counts the numbers of pass codes in each cell of a fixed grid in the image and equivalent images are located by applying the Hausdorff distance to the feature vectors.

Other researchers have also proposed methods to retrieve text directly from non-English document images. For instance, Y. He et al [22] have proposed an index and retrieval method for Chinese document images based on stroke density code. Language classification of multilingual documents is another field having been researched. A. L. Spitz et al [23-24], C. Y. Suen et al [25] and C. L. Tan et al [26] have developed systems to identify Latin-based languages, Han-based languages and other languages using the character shape coding [27].

3. Feature Extraction

Figure 1 outlines the steps in gauging the similarity of document images based on content. To identify the features, character objects in the predominant font are extracted from the document images and then character object equivalent classes are identified based on shape similarity. From several sets of classes, one unified class set can be estimated. The objects, which belong to the same class, are assumed to represent the same identity. Layout analysis is performed to determine the reading order of character objects. An object sequence can be obtained from each document image. This information is used to calculate the similarity of document images using the N-Gram algorithm.

3.1 Character Object

In document images, there are three kinds of character objects. The first is the isolated characters, that have each only one connected component. The second is also isolated characters, but they each have more than one connected component, such as lower characters "i" and "j". The third kind is the characters that are connected to each other, such as "ft" and "ff". Character objects can be extracted by measuring the connected components in the image and comparing the relative positions of adjacent components. Thus a character object contains only one connected component or several connected components, which have unambiguous relative positions.

We divide the document image into many rectangle zones and each zone contains one character line. The comparison of the relative positions of connected components is restricted to the interior of each zone. The components, which are in different zones, belong to different character objects. So, these components can be expressed as $C_{i,j}$, where *i* is the number of zone and *j* is the order number of connected components in each zone from left to right. If the horizontal overlapping extent in $C_{i,j}$ and $C_{i,j+1}$ is larger than a threshold, they belong to same character object. Otherwise, they belong to different objects.

Punctuation does not have special meaning in the N-Gram algorithm. It is wasteful to spend too much time processing punctuation marks. In general, the height of a punctuation mark is less than that

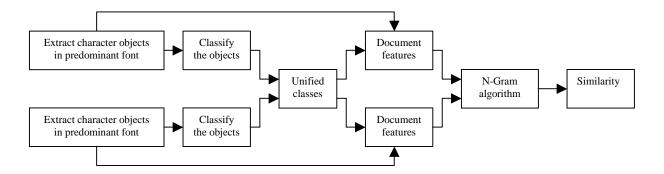


Figure 1. Gauging the similarity of document images based on content

of a character. So, when character objects have been retrieved, we do an additional operation to filter small objects whose width or height is less than a pre-determined threshold. Most of the punctuation marks and noise will be removed in this manner.

Figure 2 shows the result of character object retrieval. Item (a) is the original document image. Item (b) outlines the zones of character lines and item (c) shows the extracted character objects. TOKYO — Japan's trade ministry is hoping to produce a Japanese version of American software prodigy and entrepreneur Bill Gates by offering up to 100 million yen (S\$1.5 million) each to TOKYO — Japan's trade ministry is hoping to produce a Japanese version of American software prodigy and entrepreneur Bill Gates by offering up to 100 million yen (S\$1.5 million) each to TOKYO — Japan's trade ministry is hoping to produce a Japanese version of American software prodigy and entrepreneur Bill Gates by offering up to 100 million yen (S§1.5 million) each to

a. Original image

b. Separated line zone

c. Character objects

Figure 2. Extraction of character objects

3.2 Character Object Class

In newspapers, the text may be printed in different font sizes and font styles. The main body of text is usually printed in one font, which is generally the predominant font, whereas headings and captions may appear in a variety of fonts. For gauging similarity of document images, only text in the predominant fonts is considered. To identify characters, an unsupervised classifier is used to place each character object into a set of classes. Each class is regarded as representing a unique identity.

For each character object, we use two vectors to store the object features: Vertical Traverse Density (VTD) Vector and Horizontal Traverse Density (HTD) Vector. Samples of HTD and VTD are shown in Figure 3.

For two character objects *i* and *j*, their distance d_{ij} will be calculated by the following function:

$$d_{ij} = diff(HTD_i, HTD_j) + diff(VTD_i, VTD_j)$$
(1)

where, $diff(V_i, V_j)$ is a function to calculate the distance between the two vectors V_i and V_j . We assume that n_i and n_j are the dimensions of vectors V_i and V_j , respectively, and $V_i = v_{i0}v_{i1}v_{i2}\cdots v_{in_i-1}$, $V_j = v_{j0}v_{j1}v_{j2}\cdots v_{jn_i-1}$. The function $diff(V_i, V_j)$ is defined as follow:

$$diff(V_i, V_j) = \min_{-c \le k \le c} (distance(U_i^k, U_j^k))$$
(2)

where, c is a positive integer constant. The vector U_i^k and U_j^k have the same dimension, which is

$$n_{ij}^{k} = \begin{cases} \max(n_i + k, n_j) & \text{if } k \ge 0\\ \max(n_i, n_j - k) & \text{if } k < 0 \end{cases}$$

$$(3)$$

and their elements are

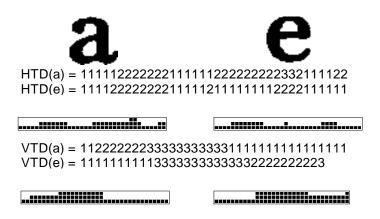


Figure 3: The illustration of HTD and VTD of character 'a' and 'e'

$$u_{il}^{k} = \begin{cases} v_{il} - \max(k, 0) & \text{if } \max(k, 0) \le l < \max(k, 0) + n_{i} \\ 0 & \text{otherwise} \end{cases}$$
(4)

and

$$u_{jl}^{k} = \begin{cases} v_{jl} - \max(-k,0) & \text{if } \max(-k,0) \le l < \max(-k,0) + n_{j} \\ 0 & \text{otherwise} \end{cases},$$
(5)

respectively.

The initial value of $d(U_i^k, U_i^k)$ is the maximum of *m* and *n*. For each $l \in (0, \min(n, m)]$, if

$$u_{il}^{k} = u_{jl}^{k}$$

or

$$u_{il}^{k} = u_{il-1}^{k} \& u_{il+1}^{k} = u_{jl}^{k}$$

or

$$u_{jl}^{k} = u_{jl-1}^{k} \& u_{jl+1}^{k} = u_{il}^{k}$$

the value of $d(U_i^k, U_j^k)$ is decreased by one.

The result of classification is shown in Figure 4. In item (a), each rectangle outlines a character object extracted and the number expresses the sequence number of the class that the object belongs to. The objects that have the same number represent the same class. Item (b) lists the total class set created from this image.

TOKYO — Japan's trade ministry is hoping to produce a Japanese version of American software prodigy and entrepreneur Bill Gates by offering up to IOD million yen (S\$1.5 million) each to

"L "O "KA "**l** "a "b "u "z "f "**r** "*G* "e ² m ¹ i ry ¹ h o 'g 'u 'c ² v 'f Am ^{**}ft ^{**}W ^{**}8Y ^{**}B ^{**}I ^{**}G ^{**}b ^{**}Y ffi ³²1 ³³0 ³⁴(³⁵S ³⁶S ³⁷5 ³⁰)

(a)

(b)

Figure 4. Character object classification

3.3 Unifying Character Object Class

One set of character object classes can be obtained from each document image. The predominant font of different images may have different font sizes. And the numbers of different sets of classes may be also different. To find a unified way to express the features of the document images in question, we must build a unified object classes among these document images.

First, the VTD vector and HTD vector of all character object classes are normalised so that the vectors of object classes with different sizes will have the same dimension number. The number of permitted dimension of vectors is set sufficiently large. All the features of VTD and HTD vectors will be preserved. Next, all elements of the normalised class sets are unified. They are classified again to create a set of unified classes. The equivalent classes of different sets are merged to one class. As a result, the equivalent objects in different document images will be denoted by one same object class. Finally, a look-up table from the original class set to the unified class set is built for each document image. Using these tables, all character objects in these document images can be mapped to the unified character object classes. Objects corresponding to the same class will be regarded as having the same identity.

3.4 The Class Number List of Character Objects

After all character objects have been expressed by a set of classes, a layout analysis is performed to determine the reading order of character objects and the space between two adjacent objects. One list is built for each document. Each item in the list is the class identification number that the character object belongs to. When the interval between two adjacent objects is very large or they belong to different lines, one element of blank class will be added as a word separator. The list so constructed will be used to measure similarity with other document images.

4. N-Gram Algorithm

The use of N-Gram algorithm for text similarity was proposed by M. Damashek [18]. The approach basically uses frequency statistics to calculate the similarity between the two vectors representing two documents. The use of N-Gram algorithm in other text processing has also been reported in [5-17]. These methods are based on the ASCII values of the electronic texts. Instead of relying on ASCII values, the use of image contents has been attempted by researchers [19-28] for summary extraction, similarity measurement and document retrieval. The present method attempts to adapt the N-Gram algorithm for image-based similarity measure.

4.1 N-Gram slice

The N-Gram slice is the basic unit to be sampled in the N-Gram algorithm. The class identification number list is converted to a set of N-Gram slices. An N-Gram is a sequence of N consecutive items of a stream. Using a window of N-item length, which is moved over the list one item forward at a time, N-Grams are copied out of the list.

4.2 Document Vector

First, every possible N-Gram is given a number, so called the hash key. How the N-Grams are numbered is not important, as long as each instance of a certain N-Gram is always given the same number, and that two different N-Grams are always assigned different numbers.

Next, a hash table is created to keep track of the frequency of occurrence in the list being studied. Each hash table can be treated as a vector, so called the document vector. Every time an N-Gram is picked, the element of the document vector given to the N-Gram is increased by one. The hash key of N-Gram determines the corresponding position of this N-Gram in the vector.

The occurrence frequency of each N-Gram is normalised by dividing it by the total number of the extracted N-Grams. This means that the absolute number of occurrence will be replaced with the relative frequencies of corresponding N-Grams. The reason for doing this is that similar texts of different lengths after this normalisation will have similar document vectors.

4.3 Similarity Measure

Document vectors for similar documents generally point in the same direction. The similarity score between two document vectors is defined as their scalar product divided by their lengths. A scalar product is calculated through summing up the products of the corresponding elements. This is equivalent to the cosine of the angle between two document vectors seen from the origin. So, the similarity between document images m and n will be

Similarity
$$(X_m, X_n) = \frac{\sum_{j=1}^{J} x_{mj} x_{nj}}{\sqrt{\sum_{j=1}^{J} x_{mj}^2 \sum_{j=1}^{J} x_{nj}^2}}$$
 (6)

where, X_m and X_n are the document vectors of image *m* and *n* respectively, *J* is the dimension number of document vector, and $X_i = x_{i1}x_{i2}\cdots x_{iJ}$.

5 Experimental results

Experiments were carried out to test the effectiveness of our image-based similarity measure in comparison with the text-based similarity N-Gram algorithm. All document images in the experiments were obtained by scanning at 600 pixels/inch (ppi). To make the process simple, some preprocessing is done by de-skewing the images [29] and removing noise such as small dirty spots. In the case where there are headlines and pictures or photographs, they are removed from the images. Four different corpora of documents were used in the following tests.

Corpus One (E01 - E26) is made up of articles that were extracted from the Internet and were already electronically available. The news articles were printed using MS-Word in 10-point Times New Roman font. The printed documents were then scanned as images. These articles address four different kinds of topic, respectively. E01-12 talk about economic crises in Brazil, E13-17 refer to personal computer, E18-E21 tell of scholarship and E22-E26 describe the news of a nuclear spy in US. For each topic, we picked the first one of each group as the reference article and thus E01, E13, E18 and E22 were selected. Similarity measures of all the articles in this corpus with the respective four reference articles were made using the image-based and text-based methods. The results are summarized in Table 1 and Figure 4.

The above images came from paper printed by a printer. We next used two corpora that came from newspapers directly and scanned them to get the images. To create the ASCII versions of these articles as a means of benchmarking, an OCR system was used to extract the text from the images. The extracted texts were corrected by hand for any error from the OCR.

Corpus Two (N1 - N8) contains eight news articles in *The Straits Times*, a local English news daily in Singapore. In this corpus, four articles talk about Indonesia, while the other fours contain news about Japan, Cambodia, Thailand and Russia, respectively. The eight articles are shown in figure 5 and pair-wise comparisons among these articles are summarized in Table 2 for both the image-based and text-based similarity. Article N1 was chosen as a reference article to compare with the rest. The result is shown in figure 6.

Corpus Three (C1 - C7) comprises recent news in *LianHe ZaoBao*, a local Chinese news daily in Singapore. In this corpus, articles C1 and C2 talk about the relationship between Singapore and Malaysia, articles C3 and C4 are about the economy of Malaysia, and articles C5 to C7 contains news about the relationship between Mainland China and Taiwan. The articles are shown in figure 7 with codes C1 to C7 indicated to help the non-Chinese readers. Image-based and text-based similarity measures among articles in corpus three are shown in table 3. Article C1 was used as a reference article to compare with the rest. The result is shown is figure 8.

From the above results, we can see that the similarities of documents measured from text-mode articles and image-based articles share some resemblance though not entirely equivalent to each other. The result of the text version of documents provides more distinguishable similarity measures. This is because the character objects extracted from the document images are not equivalent to characters and objects corresponding to the same character may be classified into different object classes. Nevertheless, the image-based similarity provides an adequate means to retrieve similar news articles with respect to a reference article. Furthermore, the results from corpus three show equally convincing similarity measures for Chinese news articles, thus confirming the language independence of our approach.

From the testing with the three corpora, it can be seen that a threshold may be set to decide whether a text is similar to a reference article. The threshold lies somewhere in the region of 0.1 to 0.2. A fourth corpus is thus chosen to see the effect of the choice of threshold. This corpus contains a total of 159 English news articles which may be roughly grouped into nine major topics depending on their contents. These articles are different from those in the above three corpora. Corpus four is a mixture of articles downloaded from the Internet and articles taken from newspaper cuttings. An article from each of the nine topics is chosen as the reference article for that topic to retrieve articles from the corpus. Knowing the number of articles in topic *i* (let it be n_i), we first allowed the system to retreive n_i topmost similar articles and determined how many of these n_i articles are about topic *i*. Let this number of correctly retrieved articles be m_i . We define *accuracy* of this retrieval process as We next retrieved articles based on the threshold instead of a pre-determined number of m_i/n_i . articles. We set threshold at 0.1, 0.15 and 0.2 in the next three experiments respectively, and find the values of precision¹ and recall² based on the usual definitions adopted in information retrieval. We carried out the above experiments for all articles, but taking one article in turn as a reference each time. The average accuracies, precisions and recalls were then obtained for each class. They are tabulated in Table 4. It can be seen that if the number of relevant articles are known beforehand, then retrieving that number of articles for a topic in question can achieve an average accuracy of 87.7%. Using a threshold as a basis of retrieval, one can see a trade-off between precision and recall. At the threshold of 0.2, the average precision and recall are 100% and 44%, respectively, whereas choosing 0.1 as the threshold will give an average precision and recall of 73.9% and 85.9%, respectively. Thus, setting a higher threshold gives a better precision but poorer recall, and the reverse is true for a lower threshold. If the emphasis is on retreiving only relevant articles, then a 0.2 threshold should be used. On the other hand, if the intent to retrieve as many as possible news articles, then a threshold of 0.1 may be adopted. The 0.15 threshold appears to be a good compromise.

6 Conclusion and Future Work

A new model of document image text retrieval based on an image-based similarity measurement without the use of OCR is proposed in this paper. We extract the features of document images by obtaining and classifying the character objects. Then, a N-Grams algorithm is used to measure their similarity. Experiments using four copora of news articles have confirmed the validity of the model with an average of precision ranging from 73.9% to 100% and an average recall ranging from 44% to 85.7%, depending on the similarity threshold.

The method is suited for gauging the similarity of document images that have the same font style. One of our future research directions is to examine documents of different font sizes and styles. The final object of our method is to use it in the retrieval of news articles from microfilm images [1]. Microfilm images are noisier than the images used in the present study. So, how to deal with the noise will also be our future research.

¹ Precision is defined as percentage of the number of correctly retrieved articles over the number of all retrieved articles.

² Recall is defined as percentage of the number of correctly retrieved articles over the number of articles in the category.

			01	E	13	E	18	E22		
		Image based	Text based	Image based	Text based	Image based	Text based	Image based	Text based	
	E01	1.0000	1.0000	0.1357	0.0543	0.0842	0.0217	0.1294	0.0589	
	E02	0.3271	0.4299	0.1053	0.0477	0.0577	0.0131	0.0854	0.0507	
	E03	0.5062	0.5554	0.1226	0.0318	0.0782	0.0227	0.1304	0.0649	
	E04	0.3886	0.4410	0.1017	0.0281	0.0563	0.0135	0.0872	0.0636	
	E05	0.7967	0.8459	0.1407	0.0443	0.0824	0.0209	0.1342	0.0505	
Group	E06	0.3425	0.4112	0.1059	0.0681	0.0445	0.0087	0.0991	0.0633	
1	E07	0.3047	0.3993	0.0761	0.0297	0.0474	0.0264	0.0976	0.0301	
	E08	0.3401	0.4303	0.1025	0.0313	0.0645	0.0194	0.1198	0.0723	
	E09	0.5030	0.6296	0.1268	0.0397	0.0740	0.0395	0.1191	0.0524	
	E10	0.1883	0.2463	0.1919	0.1290	0.1094	0.0652	0.1296	0.0572	
	E11	0.2892	0.4186	0.0971	0.0348	0.0572	0.0225	0.0992	0.0424	
	E12	0.5458	0.6635	0.1287	0.0532	0.0618	0.0191	0.1187	0.0414	
	E13	0.1357	0.0543	1.0000	1.0000	0.1018	0.0474	0.0970	0.0191	
Group	E14	0.0986	0.0348	0.2782	0.3491	0.0721	0.0299	0.0701	0.0336	
2	E15	0.1001	0.0333	0.2043	0.2959	0.0744	0.0454	0.0852	0.0580	
	E16	0.0853	0.0209	0.2364	0.3644	0.0757	0.0773	0.0625	0.0313	
	E17	0.0947	0.0347	0.2897	0.3559	0.0804	0.0441	0.0633	0.0141	
	E18	0.0842	0.0217	0.1018	0.0474	1.0000	1.0000	0.0773	0.0594	
Group	E19	0.1397	0.0562	0.1091	0.0263	0.1891	0.2917	0.0834	0.0437	
3	E20	0.1142	0.0326	0.0818	0.0344	0.1576	0.2055	0.0719	0.0380	
	E21	0.0889	0.0257	0.0750	0.0351	0.1424	0.2102	0.0675	0.0526	
	E22	0.1294	0.0589	0.0970	0.0191	0.0773	0.0594	1.0000	1.0000	
Group	E23	0.1941	0.0573	0.1556	0.0217	0.1145	0.0607	0.2288	0.2808	
4	E24	0.1691	0.0448	0.1255	0.0177	0.0832	0.0412	0.3660	0.4700	
	E25	0.1910	0.1073	0.1294	0.0299	0.1010	0.0370	0.1540	0.1834	
	E26	0.1149	0.0648	0.0856	0.0139	0.0547	0.0323	0.1281	0.1761	

 Table 1:
 Image-based and Text-based Similarity for Corpus One

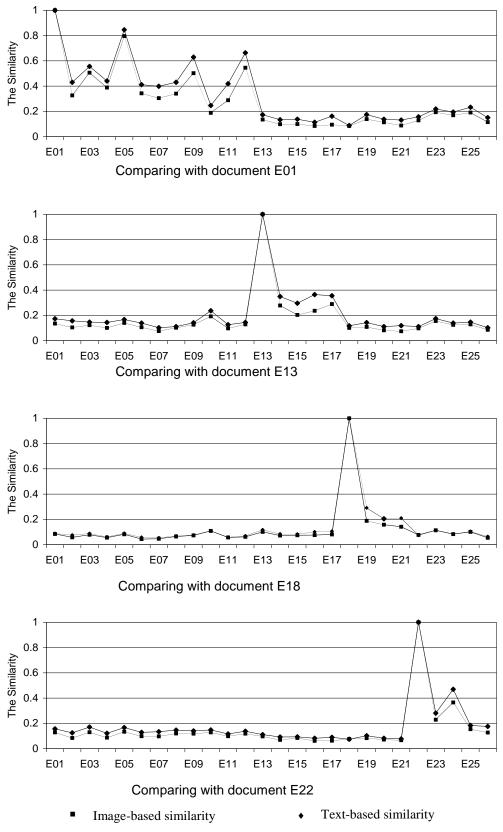


Figure 4. Comparison of Image-based and Text-based Similarity for Corpus One

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Hun Sen set to meet Plan to send more police to Dili Annan over tribunal

Cambodia is warned that the international community will not accept Khmer Rouge trials that exclude the United Nations

A mission which is beading back to New York today without an agreement on the UNTERD Nations Sec-trator Control with the second sec-tion Sea later this month to work the deally control to the second second second second second thing a minord themat to high and orthy the UN can orge regress (for the second second pairs than any second second second pairs than any second second second they and orthy the UN can orge regress (for the second table of the pairs than any second second second second pairs than any second second second second they in all orthy the UN can orge regress (for the second table of the pairs than any second second second second second pairs than any second second second second to the UN can be second second second second they in M then Second second second second second to the UN second second second second second second second to the UN second second second second second second second to the UN second second second second second second second to the UN second second second second second second second to the UN second second second second second second second the UN second secon

al" that might exclude allies leaders of the Cam-bodian Pre-micr. I think that

we are justice in ed in taking Cambodia is part in a pro-cess which long overdue.' will just UNE OVERAUE. judge one — Mr Zacklin, the U two people assistant secretary genera-in order to for legal affait crimas that have been com-mitted," he said. "I think that justice" sistance. "T think that justice" sistance. "To think that justice" sistance. "To think that justice" sistance. — Mr Zacklin, the UN assistant secretary-general for legal affairs alk was Human-umbling and the UN owends trial would

Russian graft probe moves to Switzerland

Money-laundering scandal, which may involve aid funds, prompts US congressman to say that the West should re-examine its ties with Russia

- A top Russian he added, but gave no details. has arrived in He said Mr Volkov was to look into alles - multing, whether "several He said Mr Voli probing whether ' high-placed Russia cials' were corrupt abused their office. Swiss prosecutors ready investigating corruption cases in various firms with i links, including the ap of contracts to Swi structure form. Mo

Vigilantes taking no chances

Young fighters armed with knives are back on the streets guarding their neighbourhoods as ballot boxes are brought into Dili from the regions

The young mean with by brickuit remains of his vil-ghair and the canous statet were lack in the state of the state state of the state of the state of the state is the state of the state of the state is the state of the state of the state is the state of the state state of the state of the state of the state state of the state state of the state of the state of the state state of the state of the state state state of the state state state of the state stat

of Aita

The militiamen, many red with guns, had ran-ked the office last Thurs-



y. Journalists also saw sev-where the vote count is to Aitarak members, who

after vote in East Timor Pro-integration militias renew campaign of intimidation while their leaders threaten to derail peace talks tuting "a free and peaceful and therefore fair execution of the consultation". Bu SUSAN SIM preceful preceful of the consultation." On the irregularities, which were also highlighted by government represent tives in Data A INDENT

Tensions began ris-n as East Timor hov-the brink of indepen-ollowing Monday's vote, which saw an 39 per cent turnout. hile their political threatened to derail liation talks unless

tada while their political deteriorated after political reconciliation talks unless development when suppeted million the political according to the political sector of the p

r agents t

good picture ... despite all the doomsday predictions about violence." The ground situation here deteriorated after polls closed, when suspected mili-

Jakarta rushes troops to E. Timor

Elite soldiers dispatched after UN request for protection; result of autonomy referendum out today

Australian Foreign Minist Alexander Downer that pla By SUSAN SIM BRESPONDENT With pro-integra-nilitias already in conne towns across , the authorities Unamet spokesman Da-vid Wimhurst reported yes-terday that militias in Mal-iana "rampaged through the town all night" and torched bouses, forcing UN staff to

fits East Ti-

Figure 5. Corpus Two : Articles from English newspapers

		N1	N2	N3	N4	N5	N6	N7	N8	News Title		
N1	*	1.000	0.284	0.162	0.210	0.099	0.119	0.142	0.159	Tensions rise after vote in East Timor		
INI	**	1.000	0.362	0.221	0.260	0.118	0.143	0.179	0.185	Tensions fise after vote in East Timor		
N2	*	0.284	1.000	0.192	0.235	0.104	0.112	0.121	0.148	Jakarta rushes troops to E. Timor		
112	**	0.362	1.000	0.276	0.276	0.119	0.127	0.164	0.168	Jakarta rusnes troops to E. Timor		
N3	*	0.162	0.192	1.000	0.193	0.064	0.086	0.125	0.082	Plan to send more police to Dili		
113	**	0.221	0.276	1.000	0.224	0.084	0.095	0.146	0.104	I fail to selid more police to Dili		
N4	*	0.210	0.234	0.193	1.000	0.097	0.098	0.115	0.134	Vigilantes taking no chances		
184	**	0.260	0.276	0.224	1.000	0.108	0.114	0.146	0.165	vignances taking no chances		
N5	* N5	0.099	0.104	0.064	0.097	1.000	0.089	0.081	0.091	Wanted: A Japanese Bill Gates		
145	**	0.118	0.119	0.084	0.108	1.000	0.117	0.109	0.107	wanted. A Japanese Bin Gates		
N6	*	0.119	0.112	0.086	0.098	0.089	1.000	0.120	0.092	Bangkok wants Thais to holiday at home		
140	**	0.143	0.127	0.095	0.114	0.117	1.000	0.137	0.103	Dangkok wants Thats to holiday at holid		
N7	*	0.142	0.121	0.125	0.115	0.081	0.120	1.000	0.164	Hun Sen set to meet Annan over tribunal		
1117	**	0.179	0.164	0.146	0.146	0.109	0.137	1.000	0.201	Hun Sen set to meet Allian over tribular		
N8	*	0.159	0.148	0.082	0.134	0.091	0.092	0.164	1.000	Russian graft probe moves to Switzerland		
110	**	0.185	0.168	0.104	0.165	0.107	0.103	0.201	1.000	Russian gran probe moves to Switzenand		

Table 2. Comparison of Image-based and Text-based similarity for Corpus Two

Notes:

*: Image-based Similarity

**: Text-based Similarity

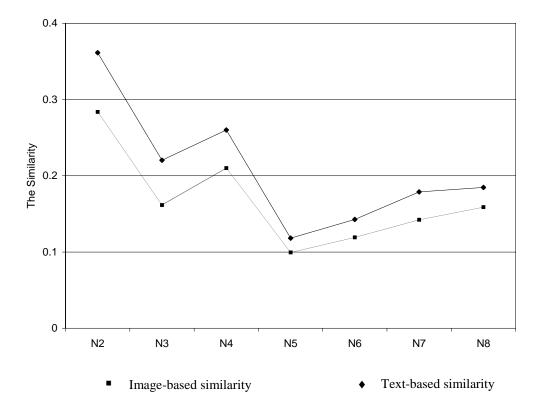


Figure 6 Comparison of image-based similarity and text-based similarity between N1 and other articles



Figure 7. Corpus Three – Articles from Chinese newspapers

Table 3. Comparison of Image-based and Text-based similarity for Corpus Three

		C1	C2	C3	C4	C5	C6	C7	Rough Translation of News Title
C1	*	1.000	0.444	0.127	0.120	0.145	0.121	0.191	Malaysia willing to compromise to resolve
	*	1.000	0.417	0.231	0.177	0.094	0.130	0.166	issues on bilateral ties with Singapore
C2	*	0.444	1.000	0.107	0.127	0.122	0.102	0.200	Foreign Minister denies impact of Umno
C2	*	0.417	1.000	0.191	0.194	0.116	0.140	0.197	election on negotiation with Singapore
C3	*	0.127	0.107	1.000	0.147	0.059	0.045	0.058	Malaysia to become shoppers' paradise in
0.5	**	0.231	0.191	1.000	0.227	0.102	0.135	0.089	three years
C4	C4 *	0.120	0.127	0.147	1.000	0.069	0.067	0.066	The second port in Johore: a catalyst for
	**	0.177	0.194	0.227	1.000	0.084	0.123	0.085	Malaysia economic development
C5	*	0.145	0.122	0.059	0.069	1.000	0.378	0.345	Beijing warns Taipei again on the need for
0.5	*	0.094	0.116	0.102	0.084	1.000	0.442	0.297	a schedule for reunification
C6	*	0.121	0.102	0.045	0.067	0.378	1.000	0.350	Analysis of the wish for reunification of
0	**	0.130	0.140	0.135	0.123	0.442	1.000	0.285	the people in China
C7	*	0.191	0.200	0.058	0.066	0.345	0.350	1.000	Talking about "Taiwan Independence"
C/	*	0.166	0.197	0.089	0.085	0.297	0.285	1.000	means war

Notes:

*: Image-based Similarity

**: Text-based Similarity

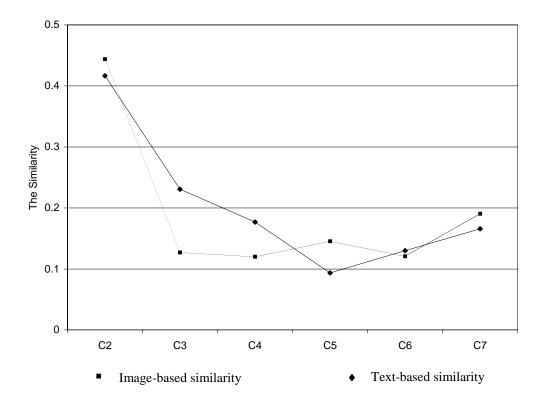


Figure 8 Comparison of image-based similarity and text-based similarity between C1 and other articles

		Average		Th	reshold = ().2	Thre	eshold $= 0$	15	Threshold $= 0.10$		
Topic id. no. <i>i</i>	No. of articles on topic i (n_i)	n_i	Accuracy %	Average similarity	Precision %	Recall %	Average similarity	Precision %		Average similarity	Precision %	Recall %
1	26	0.1292	72.9	0.2646	100	13.2	0.2097	95.3	22.1	0.1482	83.8	56.9
2	22	0.1995	94.8	0.2451	100	47.1	0.2153	98.2	75.3	0.1730	73.8	93.7
3	18	0.1981	94.0	0.2316	100	52.0	0.2068	96.9	82.1	0.1606	57.1	97.3
4	16	0.1940	88.4	0.2565	100	49.2	0.2252	96.7	68.0	0.1730	76.7	87.9
5	22	0.2013	82.9	0.2566	100	53.8	0.2303	96.5	67.9	0.1722	66.0	86.2
6	19	0.1697	86.2	0.2399	100	35.9	0.2099	98.2	59.9	0.1742	82.8	85.8
7	18	0.1578	85.0	0.2619	100	18.4	0.2006	98.0	54.2	0.1674	92.9	78.1
8	18	0.2764	97.7	0.2921	100	82.1	0.2763	97.2	96.0	0.2082	58.1	100
Ave	erage	0.1908	87.7	0.2560	100	44.0	0.2218	97.1	65.7	0.1721	73.9	85.7

Table 4. Accuracy, Precision and Recall of image-based document text retrieval for Corpus Four

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