A Robust Practical Text Summarization

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Abstract

We present an automated method of generating human-readable summaries from text documents such as news, technical reports, government documents, and even court records. Our approach exploits an empirical observation that much of the written text display certain regularities of organization and style, which we call the Discourse Macro Structure (DMS). A summary is therefore created to reflect the components of a given DMS. In order to produce a coherent and readable summary we select continuous, well-formed passages from the source document and assemble them into a mini-document within a DMS template. In this paper we describe the Summarizer-Tool, a Java-implemented prototype, and its applications in various document processing tasks.

Introduction

Perhaps the most difficult problem in designing an automatic text summarization is to define what a summary is, and how to tell a summary from a non-summary, or a good summary from a bad one. The answer depends in part upon who the summary is intended for, and in part upon what it is meant to achieve, which in large measure precludes any objective evaluation. For most of us, a summary is a brief synopsis of the content of a larger document, an abstract recounting the main points while suppressing most details. One purpose of having a summary is to quickly learn some facts, and decide what you want to do with the entire story. Therefore, one important evaluation criterion is the tradeoff between the degree of compression afforded by the summary, which may result in a decreased accuracy of information, and the time required to review that information. This interpretations is particularly useful, though it isn't the only one acceptable, in summarizing news and other report-like documents. It is also well suited for evaluating the usefulness of summarization in context of an information retrieval system, where the user needs to rapidly and efficiently review the documents returned from search for an indication of relevance and, possibly, to see which aspect of relevance is present.

Our early inspiration, and a benchmark, have been the Quick Read Summaries, posted daily off the front page of New York Times on-line edition (http://www.nytimes.com). These summaries, produced manually by NYT staff, are assembled out of passages, sentences, and sometimes sentence fragments taken from the main article with very few, if any, editorial adjustments. The effect is a collection of perfectly coherent tidbits of news: the who, the what, and when, but perhaps not why. Indeed, these summaries leave out most of the details, and cannot serve as surrogates for the full article. Yet, they allow the reader to learn some basic facts, and then to choose which stories to open.

This kind of summarization where appropriate passages are extracted from the original text is very efficient, and arguably effective, because it doesn't require generation of any new text, and thus lowers the risk of misinterpretation. It is also relatively easier to automate, because we only need to identify the suitable passages among the other text, a task that can be accomplished via shallow NLP and statistical techniques. Nonetheless, there are a number of serious problems to overcome before an acceptable quality summarizer can be built. For one, quantitative methods alone are generally too weak to deal adequately with the complexities of natural language text. For example, one popular approach to automated abstract generation is to select key sentences from the original text using statistical and linguistic cues, perform some cosmetic adjustments in order to restore cohesiveness, and then output the result as a single passage, e.g., (Luhn 1958) (Paice 1990) (Rau, Brandow & Mitze 1994) (Kupiec, Pedersen & Chen 1995). The main advantage of this approach is that it can be applied to almost any kind of text. The main problem is that it hardly ever produces an intelligible summary: the resulting passage often lacks coherence, is hard to understand, sometimes misleading, and may be just plain incomprehensible. In fact, some studies show (cf. (Rau, Brandow & Mitze 1994)) that simply selecting the first paragraph from a document tends to produce better summaries than a sentence-based algorithm.

A far more difficult, but arguably more "human-like" method to summarize text (with the possible exception of editorial staff of some well-known dailies) is to comprehend it in its entirety, and then write a summary "in your own words." What this amounts to, computationally, is a full linguistic analysis to extract key text components from which a summary could be built. The discourse-level approach, e.g., (Ono, Sumita & Miike 1994) (McKeown & Redev 1995), extracts discourse structure elements and generates the summary within this structure. The knowledge-level approach, (DeJong 1982) (Lehnert 1981) attempts to fill pre-defined summary templates with text elements obtained using information extraction techniques. While these approaches can produce very good results, they are yet to be demonstrated in a practical system applied to a reasonable size domain.

The approach we adopted in our work falls somewhere between these two extremes, although philosophically we are closer to NYT cut-and-paste editors. We overcome the shortcomings of sentence-based summarization by working on paragraph level instead. Paragraphs are generally self-contained units, more so than single sentences, and their relationships with the surrounding text are somewhat easier to trace. Our summaries are thus made up of paragraphs taken out of the original text. In order to maintain coherence, we impose some fundamental discourse constraints on the generation process, but avoid a full discourse analysis.

It has been noted, e.g., (Rino & Scott 1994), (Weissberg & Buker 1990), that certain types of texts, such as news articles, technical reports, research papers, etc., conform to a set of style and organization constraints, called the Discourse Macro Structure (DMS) which help the author to achieve a desired communication effect. News reports, for example, tend to be built hierarchically out of components which fall roughly into one of the two categories: the what's-the-news category, and the optional background category. The background, if present, supplies the context necessary to understand the central story, or in the case of a follow up story, to make the document self-contained. This organization is often reflected in the summary, as illustrated in the example below from NYT 10/15/97, where the highlighted portion provides the background for the main news:

> Spies Just Wouldn't Come In From Cold War, Files Show
>
> *Terry Squillacote was a Pentagon lawyer who hated her job. Kurt Stand was a union leader with an aging beatnik's slouch. Jim Clark was a lonely private investigator.* [A 200-page affidavit filed last week by] the Federal Bureau of Investigation says the three were out-of-work spies for East Germany. And after that state withered away, it says, they desperately reached out for anyone who might want them as secret agents.

In this example, the two passages are non-consecutive paragraphs in the original text; the string in the square brackets at the opening of the second passage has been omitted in the summary. Here the human summarizer's actions appear relatively straightforward, and it would not be difficult to propose an algorithmic method to do the same. This may go as follows:

1. Chose a DMS template for the summary, e.g., Background+News.
2. Select appropriate passages from the original text and fill the DMS template.
3. Assemble the summary in the desired order; delete extraneous words.

There is another important feature of news-like texts which this algorithm exploits implicitly, and that is their hierarchical organization. In order words, we are expecting to find one or two passages in Step 2 that would make an acceptable summary, rather than a scattering of facts as one may expect in a novel. Moreover, if such a summary passage exists, and if it requires some background information to go along with it, the latter may be expected to be nearby, most likely in an adjoining paragraph. We can therefore simplify the above algorithm by adding that the Background and News passages are preferably consecutive paragraphs. This modification reduces Step 3 to mere cosmetics.

We have applied this method to build a summarization program for news. It has been applied to a variety of news-like documents, including Associated Press newswires, articles from the New York Times, Wall Street Journal, Financial Times, San Jose Mercury, as well as documents from the Federal Register, and Congressional Record. The program is domain independent, and it can be easily adapted to most European languages. It is also very robust: we used it to derive summaries of thousands of documents returned by an information retrieval system. It can work in two modes: generic and topical. In the generic mode, it produces the summary as described above. In the topical mode, it takes a user supplied statement of interest, or topic, to derive a summary related to this topic. A topical summary is usually different than the generic summary of the same document.

Thus far there has been only one systematic evaluation performed, and it was only on an experimental basis. The evaluation focused on comprehensibility of the summaries in a document retrieval situation. Early results indicate that the summaries generated using our DMS method offer an excellent time to accuracy tradeoff. This is further confirmed by the favorable responses we received from the users.

In the following sections we describe the summarizer in more details and discuss its use in context of an information retrieval system.

Discourse macro structure of a text

Empirical studies show that certain types of texts conform to relatively simple macro discourse structures. (Rino & Scott 1994), for instance, has shown that both physics papers and abstracts align closely with the *Introduction-Methodology-Results-Discussion-Conclusion* macro structure. It is likely that other scientific and technical texts will also conform to this or similar structure, since this is exactly the structure suggested in technical writing guidebooks, e.g. (Weissberg & Buker 1990). One observation to make here is that a proper summary or an abstract should reflect the DMS of the original document. On the other hand, we need to note that a summary can be given a different DMS, and this choice would reflect our interpretation of the original text. A scientific paper, for example, can be treated as a piece of news, and serve as a basis of an un-scientific summary.

Clearly, different types of text will display different macro structures. For news-like texts, this structure appears quite simple: *Background+ What-Is-The-News*. The *Background* section covers previous events and supplies the context necessary to understand the main story. The *Background* section is optional: when the background is a common knowledge or is implied in the main news section, it can, and usually is omitted. The *WhatIsTheNews* section covers the new developments and the new facts that make the news. Both sections, which do not have to occupy continuous regions of text, can be identified by a number of features, such as content words, verb tense, proper names, etc.

We make no claims that this macro-structure is the only one possible, nor even that it accounts for a majority of news-like summaries. To establish this we would need to conduct further empirical studies. A tentative examination of various news articles and their abstracts appears to support our hypothesis.

Extracting components of a DMS

Each component of a summary DMS needs to be instantiated by one or more consecutive passages extracted from the original text. These can be paragraphs, paragraph parts, sentences, or even sentence fragments. The selection of sub-sentential elements normally requires advanced information extraction techniques (MUC5 1993) (Tipster2 1996) or statistical learning methods (Strzalkowski & Wang 1996), and could substantially increase the complexity of a summarizer. At present, our summarizer works at the paragraph level: it builds the summary out of whole paragraphs, or continuous proper subpassages. Moreover, if multiple passages are selected for a summary, those that appear as a continuous region in the original text will be strongly preferred to other combinations.[1]

The passage extraction method employed here is partially based on (Strzalkowski & Wang 1996). Initially, all eligible passages (i.e., explicitly delineated paragraphs) within a document are potential candidates for the summary. As we move through text, paragraphs are scored for their summary-worthiness. Each candidate passage is considered in context of its immediate neighbors: the ones preceding and following it. The final score for each passage, normalized for its length, is a weighted sum of a number of minor scores. In general, the weights are trainable in a supervised mode, given a corpus of texts and their summaries, or in an unsupervised mode as described in (Strzalkowski & Wang 1996). At this time, however, for the purpose of the experiments described here, the weights have been set manually.

$$score(candidate) = \frac{1}{l} \bullet \sum_{h} w_h \bullet S_h \qquad (1)$$

where S_h is a minor score calculated using metric h; w_h is the weight reflecting how effective this metric is in general; l is the length of the segment.

The exact instantiation of this formula will vary depending upon which component of the summary DMS we want to extract. In each case, the passage with the highest overall score is selected, but both the minor metrics and their weights may be different. For example, to select a passage for WhatIsTheNews component, we will be primarily interested in metrics that can gauge the density of information content in the passage; to select a passage for the Background com-

[1] We are currently revising the paragraph scoring function in order to allow a greater flexibility in selecting nonconsecutive paragraphs for summary.

ponent, we will look for evidence of its connectivity to other content-bearing passages.

Metrics used in selecting the main news sections

The following metrics are used to score passages considered for the main news section of the summary DMS. The exact formulas are still being worked out, as we experiment with various types of texts and summaries.

1. Words and phrases frequently occurring in a text are likely to be indicative about its content, especially if such words or phrases do not occur often elsewhere. Therefore a weighted frequency score, akin of *tf*idf* used in automatic text indexing is suitable. Here *idf* stands for the inverted document frequency of a term with respect to some representative control collection.

2. Title of a text is often strongly related to its content. Therefore, words and phrases from the title are considered as important indicators of content concentration within a document.

3. Noun phrases occurring in the opening sentence of any given paragraph, or those used as the subject phrases, or even the first non-trivial noun phrase, in some sentences tend to be indicative of the content. When encountered elsewhere in text, these phrases receive premium scores.

4. Words and phrases occurring in only some paragraphs are weighted more highly than those scattered across the entire document, because they are more likely to serve as discriminators of summary passages. This only makes sense if applied to terms already considered as strong content indicators (cf. steps 1-3 above). Therefore, in addition to the other scores, all terms in a passage (except for common stopwords such as articles, prepositions, pronouns, etc.) are weigh-ranked by a passage-level *tf*idf*-like formula, namely *tpf*ipf*, where *tpf* is the term frequency within a paragraph, and *ipf* is an inverted passage frequency. The *ipf* score is best interpreted as N/pf, where *pf* is the number of passages containing the term and N is the total number of passages contained in the document.[2]

5. Paragraphs that are closer to the beginning of a news report tend to be more content-loaded than those towards the end. This ordering may be reversed in editorial-like texts. Therefore, the position of each passage carries an additional score. We may note here that position scoring is appropriate in generic summarization, but arguably not in topic-based summarization, where themes which are not necessarily central to the original text need to be summarized. In generic summarization this score is set up so that the summary-worthiness of paragraphs is decreasing as we read deeper into the text. In practice, our system never looks beyond 6-7 paragraph (on average).

6. Certain cue phrases explicitly suggest that what follows is in fact a summary or the main point of an article. These passages should therefore be preferred for selection. Examples of such cue phrases include: "In summary", "To sum up", "The point is", etc.

Considering the above points, particularly 1 through 4, it is easy to see the process of passage selection as closely resembling query-based document retrieval. The "documents" here are the passages (paragraphs), and the "query" is a set of words and phrases found in the document's title and in the openings of some paragraphs. Since our goal is to select one or two paragraphs from the original text, "query terms" that occur in many paragraphs are less valuable discriminators than those occurring in only a few - hence the *ipf* measure described in 4. We should also note that the summarizer allows for multi-paragraph passages to be considered as units, which is useful in texts with very short physical paragraphs (e.g., some types of newswire articles.)

Metrics used in extracting passages for the Background section

The background section supplies information that makes the summary self-contained. A passage selected from a document may have significant links, both explicit and implicit, to the surrounding context, which if severed are likely to render the passage uncomprehensible, or even misleading. A good example is the following passage:

> "Once again this demonstrates the substantial influence Iran holds over terrorist kidnapers," Redman said, adding that it is not yet clear what prompted Iran to take the action it did.

Adding a background paragraph makes this a far more informative summary:

> Both the French and Iranian governments acknowledged the Iranian role in the release of

[2]It should be noted that passages could be single paragraphs, multiple paragraphs, or some other combinations.

the three French hostages, Jean-Paul Kauffmann, Marcel Carton and Marcel Fontaine.

"Once again this demonstrates the substantial influence Iran holds over terrorist kidnapers," Redman said, adding that it is not yet clear what prompted Iran to take the action it did.

Below we list some of the criteria we consider to decide if a background passage is required, and if so, how to find one.

1. One indication that a background information may be needed is the presence of significant outgoing references, such as anaphors. For example, when the main content-bearing passage selected for the summary begins with, say, "*He* also said that..." or "In the report released Monday, FBI said that *the three* were ...", or "Once again *this* demonstrates ...", we may need to supply an extra passage to anchor the anaphors. In order to minimize the possibility of confusion with a local (intra-passage) anaphor, we require that a pronoun or a definite noun phrase occur within first N (=6) words of the passage to be considered.

2. Another way to deal with dangling coreferences is to resolve them, for instance by replacing the pronoun with the name, e.g., "President Clinton". This is acceptable only if there is no other background information required from the anchoring passage. At this time, our summarizer does no explicit reference resolution.

3. Dates and verb tenses may help to identify background information. Specifically, a tense shift from present to past, or the use of certain temporal adverbs, e.g., "now", "before", "used to", etc. often indicate the changing temporal perspective in the narrative.

4. Experiments performed at Cornell (Salton, etc. 1994) show that passages within a long document display varying degrees of interconnectivity in terms of shared vocabulary, which includes the choice of words and word forms. In this respect, background information sections tend to stand out as a relatively isolated cluster. This metric is not implemented in the current version of the summarizer, but it may be required for processing structurally complex documents, such as editorials or patent applications.

5. We have observed that the background sections tend to have more proper names than other passages.

Generating the summary

The process of assembling DMS components into a summary depends upon the complexity of the discourse structure itself. For news or even for scientific texts mentioned above, it may be just a matter of concatenating components together with, possibly a little of "cohesiveness glue", which may include deleting some obstructing sentences, expanding acronyms, adjusting verb forms, etc. In a highly specialized domain (e.g., court rulings) the final assembly may be guided by a very detailed pattern or a script that conforms to specific style and content requirements. We believe that such patterns can be acquired automatically by comparing the original documents to their hand-generated summaries.

Implementation and evaluation

The summarizer has been implemented in Java as a demonstration system, primarily for news summarization. In general we are quite pleased with the system's performance. The summarizer is domain independent, and can effectively process a range of types of documents. The summaries are quite informative with excellent readability. They are also quite short, generally only 5 to 10% of the original text and can be read and understood very quickly. The following is an abstract generated from another article appearing in the New York Times.

DOCUMENT TITLE:

Hometown Recalls Tsongas as Hero Who Inspired Renewal, Pride

GENERIC SUMMARY:

Because of Tsongas' vision, Lowell, an industrial city of 103,000 people about 25 miles northwest of Boston, has a national historic park that draws thousands of tourists each year, a minor league baseball team, a new stadium on the way, a Sheraton hotel, 14 new schools, thousands of jobs and, as important as all the bricks and dollars, renewed civic pride. "He made it cool to be from Lowell," said James Cook, one of the former senator's legions of hometown friends and director of the Lowell Plan and the Lowell Development Finance Corp., a nonprofit economic development group started by Tsongas. "Twenty-two years ago, you used to say you lived north of Boston. Now you say you're from Lowell, and proud of it."

The highlighted part is the *Background* section. The next example shows a summary where no separate background section has been generated.

DOCUMENT TITLE:

Gore Dreams of More Than Four More Years

GENERIC SUMMARY:

People who have watched Gore throughout his career had never seen him so animated. It was a good beginning to a crucial week for him. For four more years is not enough for Gore. He dreams of 8 or 12 more.

We have included the summarizer as a helper application within the user interface to an information retrieval system. In this application, the summarizer is used to derive query-related summaries of documents returned from database search. The summarization method used here is the same as for generic summaries described thus far, with the following exceptions:

1. The passage-search "query" is derived from the user's document search query rather than from the document title.
2. The distance of a passage from the beginning of the document is not considered towards its summary-worthiness.

Thus obtained topical summaries are read by the users to quickly decide the relevance of a document and, if desired, to expand their search query by pasting the summaries into it. This method has been shown to produce significantly more effective queries. The following examples illustrate a topical (query-guided summary) and compares it to the generic summary.

TOPIC:

Evidence of Iranian support for Lebanese hostage takers

DOCUMENT TITLE:

Arab Hijackers' Demands Similar To Those of Hostage-Takers in Lebanon

TOPICAL SUMMARY:

Mugniyeh, 36, is a key figure in the security apparatus of Hezbollah, or Party of God, an Iranian-backed Shiite movement believed to be the umbrella for factions holding most of the 22 foreign hostages in Lebanon.

GENERIC SUMMARY:

The demand made by hijackers of a Kuwaiti jet is the same as that made by Moslems holding Americans hostage in Lebanon - freedom for 17 pro-Iranian extremists jailed in Kuwait for bombing U.S. and French embassies there in 1983.

Summarization-based query expansion

We used our automatic text summarizer to derive query-specific summaries of documents returned from the first round of retrieval. The summaries were usually 1 or 2 consecutive paragraphs selected from the original document text. The purpose was to show to the user, by the way of a quick-read abstract, why a document has been retrieved. If the summary appeared relevant and moreover captured some important aspect of relevant information, then the user could paste it into the query, thus increasing the chances of a more successful subsequent search. Note that it wasn't important if the summarized documents were themselves relevant, only if they contain passages that could help to guide further search.

We evaluated summary-based query expansion at the Text Retrieval Conference (TREC-6). A preliminary examination of TREC-6 results indicates that this mode of expansion is at least as effective as the purely manual expansion which required the users to read entire documents and select passages for query expansion. This is a very good news, since we now appear to be a step closer to an automatic expansion. The human-decision factor has been reduced to an accept/reject decision for expanding the search query with a summary.

Other options include using the summaries of retrieved documents to quickly judge their relevance. These relevance judgements can be provided as an input to automatic relevance feedback, or they may simply help the user to select a few strongly relevant documents to work with. Naturally readable, highly compressed summaries, as these generated by our system, are excellent for this purpose, since they allow the searcher to review many documents in a fraction of time it would require to read full text.

Conclusion

Readability and brevity of summaries are critical for their usefulness to the user, along with informativeness and the ability to capture the right aspects of the content. If the main purpose of having summaries is to save the user some time, then their comprehensiveness plays a secondary role – the user can always refer to the original text for details.

We have developed a method to derive quick-read summaries from news-like texts using a number of shallow NLP and simple quantitative techniques. The summary is assembled out of passages extracted from the original text, based on a pre-determined DMS template. This approach has produced a very efficient and robust summarizer.

Immediate development plans will concentrate on improving quality of the summaries by implementing additional passage scoring functions. Further plans include handling more complex DMS's, and adaptation of the summarizer to texts other than news, as well as to texts written in foreign languages.

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APPENDIX: Sample Documents

[Excerpted from New York Times on-line edition, March 1997]

Gore Dreams of More Than Four More Years

CHICAGO - "This two-headed monster of Dole-Gingrich," Vice President Al Gore declared on Sunday afternoon, a sparkle in his eyes, a sinister tone in his voice, his entire body in motion, "has launched an all-out assault on decades of progress on behalf of working men and women."

Gore had struck a chord. His friendly audience of labor delegates to the Democratic National Convention rose, and hissed and booed the Republican demons.

The vice president stood on the podium with the kind of broad, natural grin that comes easily to most other politicians. Then the crowd began to chant, "Four more years!"

People who have watched Gore throughout his career had never seen him so animated. It was a good beginning to a crucial week for him. For four more years is not enough for Gore. He dreams of 8 or 12 more.

But to fulfill his dream of being elected president in the year 2000, the 48-year-old Gore may have to dispel the rap against him that his style is too flat and wooden to generate enthusiasm among voters.

The convention here is a big chance to do that. He has appearances scheduled across the city all week and two addresses to the convention itself, one on Wednesday night, just before President Clinton's name is placed in nomination, and again on Thursday night, when he himself accepts the nomination for another term as vice president.

[...]

[Excerpted from New York Times On-line edition, March 1997]

Hometown Recalls Tsongas as Hero Who Inspired Renewal, Pride

LOWELL, Mass. - To most people beyond this city, Paul Tsongas was the man with the odd voice who made a quixotic run for the presidency in 1992. No one really believed that Tsongas was going to be president.

To Lowell, he was the favorite first son whose extraordinary relationship with this once dying mill town transformed it, and the people who live here. The local newspaper, The Sun, made Tsongas' legacy clear in Sunday's front-page obituary: "He leaves his family and the city he resurrected."

Because of Tsongas' vision, Lowell, an industrial city of 103,000 people about 25 miles northwest of Boston, has a national historic park that draws thousands of tourists each year, a minor league baseball team, a new stadium on the way, a Sheraton hotel, 14 new schools, thousands of jobs and, as important as all the bricks and dollars, renewed civic pride.

"He made it cool to be from Lowell," said James Cook, one of the former senator's legions of hometown friends and director of the Lowell Plan and the Lowell Development Finance Corp., a nonprofit economic development group started by Tsongas. "Twenty-two years ago, you used to say you lived north of Boston. Now you say you're from Lowell, and proud of it."

Tsongas, a Democrat who died of pneumonia on Saturday at the age of 55 after a long battle with cancer, went to Washington as a U.S. representative in 1975, and was elected to the Senate in 1978. He stunned nearly everybody in 1984 when he decided to retire after one term because of his cancer. But he never left Lowell or, in a way, his first job in politics as a Lowell city councilor.

[...]

[Excerpted from Associated Press wire, June, 1988]

Arab Hijackers' Demands Similar To Those of Hostage-Takers in Lebanon

The demand made by hijackers of a Kuwaiti jet is the same as that made by Moslems holding Americans hostage in Lebanon - freedom for 17 pro-Iranian extremists jailed in Kuwait for bombing U.S. and French embassies there in 1983.

The Arab hijackers forced the airliner to fly to Iran on Monday.

Their nationality and identity remain unknown, but speculation arose that they might be part of an Iranian-linked network of terrorists.

Kuwait, a small, oil-rich desert emirate caught in the crossfire of the Iran-Iraq war, refuses to free any of the 17 prisoners and reiterated Tuesday that Kuwait will not bow to "blackmail."

The passengers and crew held hostage aboard Kuwait Airways Flight 422 have apparently become pawns in a war between followers of Ayatollah Ruhollah Khomeini and foes of his Islamic revolution.

The same could be said about Terry Anderson, chief Middle East correspondent for The Associated Press, and educator Thomas Sutherland, two Americans held captive in Lebanon since 1985.

[...]

Mugniyeh, 36, is a key figure in the security apparatus of Hezbollah, or Party of God, an Iranian-backed Shiite movement believed to be the umbrella for factions holding most of the 22 foreign hostages in Lebanon.

His family has been long linked with the Hamadis, another Shiite clan involved in kidnappings.

U.S. authorities identified Mugniyeh and Mohammed Ali Hamadi, held in West Germany on charges of smuggling explosives, as two of the four Lebanese Shiites involved in the June 1985 hijacking of a TWA airliner in which U.S. Navy diver Robert Dean Stethem was killed.

[...]