# Hybrid Page Layout Analysis via Tab-Stop Detection

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## Abstract

*A new hybrid page layout analysis algorithm is proposed, which uses bottom-up methods to form an initial data-type hypothesis and locate the tab-stops that were used when the page was formatted. The detected tab-stops, are used to deduce the column layout of the page. The column layout is then applied in a top-down manner to impose structure and reading-order on the detected regions.*

*The complete C++ source code implementation is available as part of the Tesseract open source OCR engine at http://code.google.com/p/tesseract-ocr.*

## 1. Introduction

*Physical* Page layout analysis, one of the first steps of OCR, divides an image into areas of text and non-text, as well as splitting multi-column text into columns. This paper does not address *logical* layout analysis, which detects headers, footers, body text, numbered lists, and segmentation into articles.

Physical Layout Analysis is essential to enable an OCR engine to process images of arbitrary pages, such as from books, magazines, journals, newspapers, letters, and reports. Methods for physical layout analysis fall roughly into two categories:

*Bottom-up* methods are both the oldest [1] and more recently published [2,3] methods. They classify small parts of the image (pixels, groups of pixels, or connected components), and gather together like types to form regions. The key advantage of bottom-up methods is that they can handle arbitrarily shaped regions with ease. The key disadvantage is that they struggle to take into account higher-level structures in the image, such as columns. This often leads to over-fragmented regions.

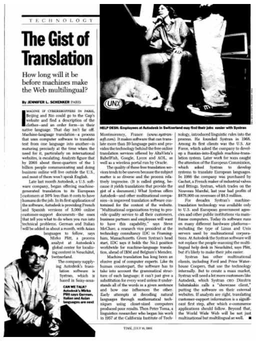
*Top-down* methods [4] cut the image recursively in vertical and horizontal directions along whitespaces that are expected to be column boundaries or paragraph boundaries. Although top-down methods have the advantage that they start by looking at the largest structures on the page, they are unable to handle the variety of formats that occur in many magazine pages, such as non-rectangular regions and cross-column headings that blend seamlessly into the columns below.

A third type of method [5-7] is based on analysis of the whitespace in an image. This solves some of the flaws in the recursive top-down methods, by finding gaps between columns by a bottom-up analysis of the gaps, looking explicitly for white rectangles. These algorithms mostly still suffer from the problem of being unable to handle non-rectangular regions.

## 2. Page layout via tab-stop detection

When a page is laid out, either by a professional publishing system, or by a common word processor, the regions of a page are bounded by *tab-stops*. The margins, column edges, indentation, and columns of a table are all placed at fixed x-positions at which edges or centers of text lines are aligned vertically. Tab-stops distinguish tables from body text, and they also bound rectangular non-column elements, such as inset images and pull-out quotes.

The tab-stops in the example of Fig. 1 are the column boundaries with an additional tab-stop for the paragraph indentation that is not required for finding the page layout. The non-rectangular inset image, typically, strays outside of the column boundaries.



TECHNOLOGY

The Gist of Translation

How long will it be before machines make the Web multilingual?

By JENNIFER L. SCHENKER PARIS

IMAGINE IF CYBERSHOPPERS IN PARIS, Beijing and Rio could go to the Gap's website and find a description of the clothes—and an order form—in their native language. That day isn't far off. Machine-language translation—a process that uses computer software to translate text from one language into another—is maturing precisely at the time when the need for it, particularly on international websites, is escalating. Analysts figure that by 2005 about three-quarters of the 1 billion people communicating and doing business online will live outside the U.S., and most of them won't speak English.

Late last month Autodesk, a U.S. software company, began offering machine-generated translation to its European customers at 50% less than it costs to have humans do the job. In its first application of the software, Autodesk is providing French and Spanish versions of 5,000 online customer-support documents—the ones that tell you what to do when you run into technical problems. German and Italian will be added in about a month, with Asian languages to follow, says Mirko Plitt, a process analyst at Autodesk's global center for localizing content in Neuchâtel, Switzerland.

The company supplying Autodesk's translation software is Systran, which is based in Soisy-sous-Montmorency, France (www.systransoft.com). It makes software that can translate more than 20 language pairs and provides the technology behind the free online translation services offered by AltaVista's BabelFish, Google, Lycos and AOL, as well as a wireless portal run by Oracle.

The quality of these free translation services tends to be uneven because the subject matter is so diverse and the process relatively imprecise. (It is called gisting, because it yields translations that provide the gist of a document.) What Systran offers Autodesk—and other multinational companies—is improved translation software customized for the context of the website. "Multinational organizations trying to provide quality service to all their customers, business partners and employees will want to have this capability," says Steve McClure, a research vice president at the technology consultancy IDC in Framingham, Massachusetts. Given Systran's head start, IDC says it holds the No.1 position worldwide for machine-language translation, ahead of IBM and Belgium's Mendez.

Machine translation has long been an elusive goal of computer experts. Like its human counterpart, the software has to take into account the grammatical structure of each language; it can't just give a substitution for every word unless it understands all of the words in a given sentence and how one influences the other. Early attempts at decoding natural languages through mathematical techniques using closet-sized computers produced poor results. Then Peter Toma, a linguistics researcher who began his work in 1957 at the California Institute of Technology, introduced linguistic rules into the process. He founded Systran in 1968. Among its first clients was the U.S. Air Force, which asked the company to develop a Russian-into-English machine-translation system. Later work for NASA caught the attention of the European Commission, which asked Systran to develop systems to translate European languages. In 1986 the company was purchased by Gachot, a French maker of industrial valves and fittings. Systran, which trades on the Nouveau Marché, last year had profits of $876,000 on revenues of $8.5 million.

For decades Systran's machine-translation technology was available only to U.S. and European government agencies and other public institutions via mainframe computers. Today its software runs on many different hardware platforms—including the type of Linux and Unix servers used by multinational corporations. At Autodesk the Systran software will not replace the people manning the multilingual help desk in Neuchâtel, says Plitt, but it's likely to make their jobs easier.

Systran has other multinational clients, including Ford and Price Waterhouse Coopers, that use the technology internally. But to create a mass market, Systran will need a lot more customers like Autodesk, which Systran CEO Dimitris Sabatakakis calls a "showcase client," putting the software on their external websites. If analysts are right, translating customer-support information is a significant first step, after which e-commerce applications should follow. Beyond that, the World Wide Web will be not just multinational but multilingual as well. ■

HELP DESK: Employees at Autodesk in Switzerland may find their jobs easier with Systran

CAN WE TALK? Autodesk's Mirko Plitt says German, Italian and Asian languages are next

TIME, JULY 30, 2001

**Fig.1. Input image.**

In some sense, white rectangles match tab-stops, but white rectangles may be disrupted by background noise or background images. Also the ends of white rectangles do not match the ends of the region bounded by the tab-stops, because the white rectangles run on into the perpendicular whitespace.

The proposed algorithm is similar to the whitespace rectangle methods in that it uses a bottom-up method to find a top-down structure, but instead of finding the space between columns, it looks for the tab-stops that mark their edges, and, through further combination of bottom-up and top-down methods, copes easily with non-rectangular regions.

There are for main phases: preprocessing, in which bottom-up morphological and connected component analysis form initial hypotheses over the local data types; bottom-up tab-stop detections; finding the columns layout; and finally applying the column layout to create an ordered set of typed regions. These phases will be detailed in sections 3-6.

## 3. Preprocessing

The aim of the preprocessing step is to identify line separators, image regions, and separate the remaining connected components into likely text components and a smaller number of uncertain type.

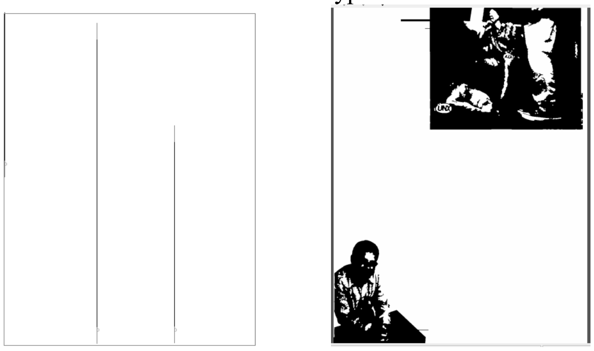


Fig.2. (a) Vertical lines, (b) Image elements.

Starting with the image of Fig. 1, the morphological processing from Leptonica [8] detects the vertical lines shown in Fig. 2(a) and the image mask shown in Fig. 2(b). These detected elements are subtracted from the input image before passing the cleaned image to connected component analysis.

The connected components (CCs) are filtered by width, *w*, and height, *h* into small, medium, and large sizes as follows: CCs with $h < 7$ (at 300ppi) are small. The 75th percentile of the heights of the remainder, $h_{75}$, is computed, and CCs with $h < h_{75}/2$ are small; $h > 2h_{75}$ or $w > 8h_{75}$ are large, and the rest are medium.

This filtration is important, since small CCs (noise or diacriticals) and large non-text CCs, (line drawings, logos, or frames) are likely to confuse the text-line algorithms, but large text headings are important to reading order detection. Large CCs are considered text at this stage if there is a left or right neighbor that has a similar stroke width. On “stressed” fonts, the stroke width is greater on vertical lines than on horizontal lines, so stroke width is calculated separately in both directions. Stroke width is calculated from horizontal and vertical local maxima of the distance function on the binary image of the CC. Fig. 3 shows the CCs are filtered as medium or large text.

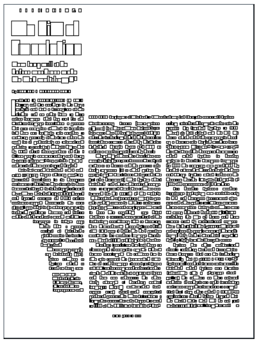


Fig.3. Filtered CCs

## 4. Finding tab positions as line segments

The process of finding tab-stop line segments has several major sub-steps: candidate tab-stop CCs that look like they may be at the edge of a text region are found and then grouped into tab-stop lines, then connections between tab-stop lines are found, enabling removal of false positives.

### 4.1. Finding candidate tab-stop components

The initial candidate tab-stop CCs are found by a radial search starting at every filtered CC from preprocessing. Assuming that the CC is at a tab-stop, the search looks for aligned neighbors and neighbors in the gutter where there should be a space. Each CC is processed independently and marked according to whether it is a candidate left tab, right tab or neither. Fig. 4(a) illustrates the candidate tab-stop CCs.

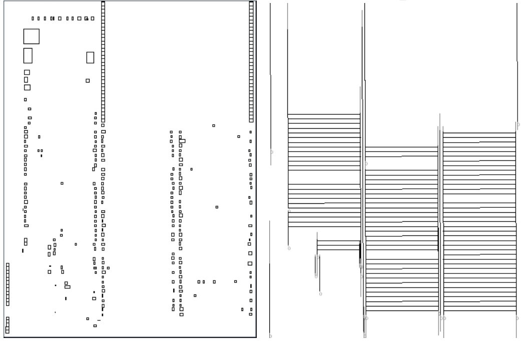


Fig.4. (a) Candidate tab-stop components (b) Fitted tab lines and traces connections.

### 4.2. Grouping candidate tab components

Candidate tab CCs are grouped into lines, and, where there are sufficiently many CCs in a group, they are kept. A least median of squares algorithm is used to fit a line to the appropriate (left or right) edge of each CC in a group. After finding all tab-stop line segments, all the lines are refitted to the page-mean direction, such that all the member tab CCs fall to one side of the line segment.

### 4.3. Tracking text lines to connect tab stops

The next step connects tab-stops by tracking text lines from one tab-stop to another. Closely adjacent, vertically overlapping CCs qualify, but large gaps cannot be jumped. Tab-stops that have a text-line connecting them are associated with each other, as being likely opposite sides of a text column. Fig. 4(b) shows the tab-stop lines and connecting text lines. Tab-stop lines that have no connection are discarded.

The most frequently occurring widths of the text lines connecting tab stops are recorded for use in finding the column layout.

### 4.4. Cleaning up tab stop ends

The final step attempts to make connected tab lines end at the same y coordinate, by allowing the ends to move between the last member CC whose edge was used for the tab line, and the first non-member CC that the line intersects. Fig. 5 shows the final tab line segments.

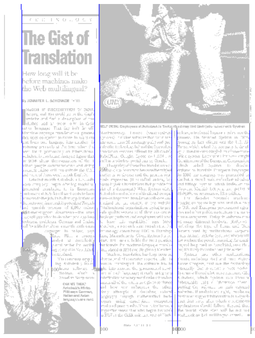


**Fig.5. Cleaned tab-stops.**

After construction of the tab stops, the CCs are re-classified, as “Text” or “Unknown” using the same text-line tracing algorithm as was used above to find connections between tab stops. If a group of CCs of significant width form a text line, then they are classified as text. Artificial image CCs of about the same size as the body-text CCd are created from the image mask from the morphological preprocessing.

## 5. Finding the column layout

The next major step is to find the column layout of the page. All the rest of the steps make use of the Column Partition (CP) objects which are created now.

Scanning the CCs from left to right and top to bottom, runs of similarly classified (text, image, or unknown) CCs are gathered into CPs, subject to the constraint that no CP may cross a tab stop line. Fig. 6 shows the result of this process. A collection of CPs from a single horizontal scan are stored in a Column Partition Set (CPset).

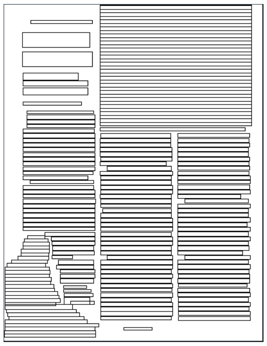


**Fig.6. Column Partitions (CPs)**

Each CPset is potentially a division of the page into columns at that vertical position. Finding the column layout is therefore a process of finding an optimal set of CPsets that best "explains" (see below) all the CPsets on the page, but first some definitions:

A *good* CP either touches a tab line on both vertical edges of its bounding box, or its width is close to a frequently occurring width. (See 4.3.)

The *coverage* of a CPset is the total width of all the good CPs that it contains.

CPset A *is better than* CPset B if A has greater coverage, or equal coverage, but more good CPs, or equal good CPs, but more total CPs.

CPset A *explains* set B **unless** one or more of the following are true:

1. The edge of one of B's CPs lies outside of all of A's CPs. This is not allowed, as it shows that B has more text than A.
2. The edges of one of B's CPs fall in different CPs of A, and the width of the B CP is a common one. This means that A has split a column of common width.
3. The right edge of one of B's CPs falls in the same A CP as the left edge of the next B CP, and the B CPs are of roughly the same width. It looks like A has a different number of columns to B. The same-width condition allows A to explain B with a pull-out.
4. Both edges of two CPs of B fall in the same CP of A. This means that A has merged two columns of B.

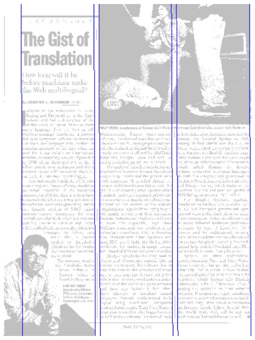


**Fig.7. Columns.**

Note that the two edges of one of B's CPs are allowed to fall into two CPs of A, as long as the width is not a common one. This allows headings that merge columns in B to be explained by A.

A list of column candidates is made from the set of CPsets on the page, ordered best first, and with duplicates eliminated by the A explains B rules above. In this process, all image CPs are ignored.

After the initial candidates are made, they are improved by adding new CPs and widening existing CPs, by using the edge of a CP in a different CPSet while widening doesn't cause overlap of CPs.

An iterative process then labels the longest segment of consecutive (allowing for a very small region of failure) page y-coordinates that is explained by one of the column candidates. Fig. 7 shows the result of this process.

## 6. Finding the regions

After the columns are found, CPs are given a type according to how many columns they span. CPs within a single column are *flowing*, partitions that touch more than one column, but do not span to the outer edges of either are *pull-out*, and partitions that completely span more than one column are *heading*.

### 6.1. Create flows of CPs

Each CP chooses its best matching upper and lower partner, being the vertically nearest CP that overlaps horizontally. Since each CP registers itself with its chosen partner, each CP may have zero or more registered upper and lower partners.

The size of the list of registered partners is forced to become zero or one for each of upper and lower, using the following rules in order:

1. Type. If there are multiple types, text can only stay with its own (exact) type, whereas image can stay with any other image type.
2. Transitive partner shortcuts are broken. If A has 2 partners B and C, and also B has C as a partner in the same direction, then delete C as a partner of A, leaving a clean chain A-B-C. Also if A has a partner B, and B has a partner A in the same direction, break the cycle.
3. (Text only) If A still has 2 partners B, C, chase B and C's partners to see which has the longest chain. Delete from A the partner that has the shortest chain, and convert the type of the shortest chain to pull-out.
4. (Image only) Choose the partner CP with the largest horizontal overlap.

All CPs now have 0 or 1 partners. Even so, (re)run rule 1 above. This purifies all chains of text to a single type and splits text chains from image chains. Image chains are purified by setting all CPs in a chain to the most general type in the chain. Fig. 8 shows the final typed CPs, where flowing text is blue, heading text is cyan, heading image is magenta, and pull-out image is orange.

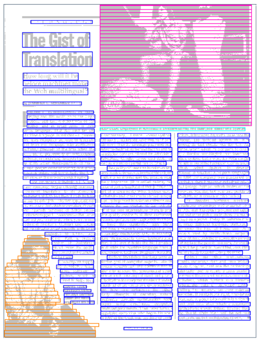


**Fig.8. Typed partition chains.**

Chains of text CPs are further divided into groups of uniform line-spacing, which make text blocks. Now each chain of CPs represents a candidate region, but the regions have to be ordered.

### 6.2. Reading order determination

Recall that image and text partitions are typed as one of 3 possibilities: flowing, pull-out, and heading. Also, the page is divided into sections of a consistent column layout. With this information, a reasonable reading order drops out of a few simple rules:

1. Flowing blocks follow by y position within a column.
2. Pull-out blocks follow by y position in an imaginary column between the real columns that they touch.
3. A heading spans multiple columns and follows anything that is above it in the columns spanned, or between them. Anything that lies in the same columns below the heading follows after it.
4. A change in column layout works just like a heading. Anything in any columns that are changed (or between them) goes before anything in the new columns. Unchanged columns are unaffected by a change in column layout.
5. Between headings, the content of columns is ordered from left to right.

### 6.3. Find the polygon boundary for each region

For simplicity of implementation, the region polygons are isothetic: i.e. edges alternate between being horizontal and parallel to the mean tab line (Approximately vertical.) The polygon edges are chosen to minimize the number of vertices, while satisfying the constraint that all CPs are contained within their region polygon, and no CP from another region intersects. Fig. 9 shows the final blocks created for the input image of Fig. 1.

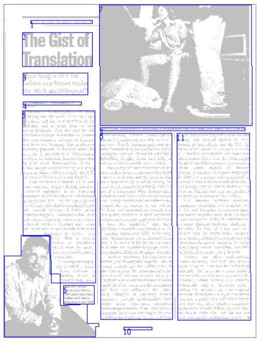


**Fig.9. Final blocks.**

## 7. Testing and results

The algorithm described herein is implemented in C++, and the source code is available as part of the Tesseract open source OCR system [9,10]. It runs on a typical 8MPixel image in approximately 1 second on a 3.4 GHz Pentium 4.

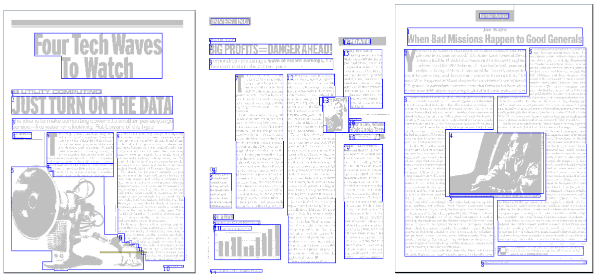


**Fig.10. Results on some of the ICDAR2007 set.**

Properly testing page layout analysis is a difficult problem [11] with very little publicly available ground-truth for complex magazine pages. The UNLV test set [12], only measures text regions, and counts errors unless figure captions are placed after all the body text.

The ICDAR page layout analysis competitions provide better measurement of overall accuracy, and the results of this algorithm appear in the 2009 competition [13]. Some graphical results are shown in Fig. 10 and numerical comparisons with the entrants in the ICDAR 2007 competition are shown in Table 1. The results in Table 1 are computed on only the 2007 test set, and the author would like to thank Apostolos Antonocopoulos for providing these results. For details on the testing methodology, see references [11] and [13].

**Table 1. Results on the ICDAR 2007 set.**

| Method | Noise | Sep | Text | Image | Overall |
|---|---|---|---|---|---|
| | | PRImA Metric | | | |
| 2007-Besus | 86.8% | 76.9% | 37.4% | 42.5% | 35.9% |
| 2007-TH1 | 68.0% | 79.7% | 76.1% | 46.2% | 67.6% |
| 2007-TH2 | 67.6% | 79.6% | 72.9% | 48.4% | 65.7% |
| Tesseract | 65.6% | 74.1% | 72.1% | 55.3% | 68.4% |
| | | F-Measure | | | |
| 2007-Besus | 62.9% | 76.2% | 95.8% | 57.2% | 90.2% |
| 2007-TH1 | 79.2% | 80.7% | 91.9% | 72.1% | 88.2% |
| 2007-TH2 | 79.2% | 80.6% | 92.3% | 72.4% | 88.6% |
| Tesseract | 79.2% | 70.9% | 93.3% | 82.0% | 91.3% |
| | | Recall | | | |
| 2007-Besus | 65.7% | 71.7% | 94.9% | 67.0% | 88.2% |
| 2007-TH1 | 65.6% | 79.5% | 96.9% | 66.4% | 89.8% |
| 2007-TH2 | 65.6% | 79.5% | 97.2% | 66.9% | 90.2% |
| Tesseract | 65.6% | 81.4% | 97.9% | 76.5% | 93.8% |
| | | Precision | | | |
| 2007-Besus | 60.4% | 81.3% | 96.7% | 50.0% | 92.2% |
| 2007-TH1 | 100.0% | 81.9% | 87.4% | 79.0% | 86.7% |
| 2007-TH2 | 100.0% | 81.7% | 87.9% | 79.0% | 87.0% |
| Tesseract | 100.0% | 62.8% | 89.0% | 88.3% | 88.9% |

## 10. Conclusion and further work

Tab-stops make an interesting and useful alternative to white rectangles for finding the column structure of a page. Combining the top-down concept of column structure with bottom-up classification methods enables page layout analysis to easily handle the complex non-rectangular layouts of modern magazine pages without losing sight of the “bigger picture” that often happens when bottom-up methods are used alone.

The algorithm described has no table detection or analysis, but the tab-stops make particularly useful features for both, so table analysis will be added in the future.

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