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Notes

A linear-time component-labeling algorithm using contour tracing technique

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9 Abstract

10 A new linear-time algorithm is presented in this paper that simultaneously labels con-
11 nected components (to be referred to merely as components in this paper) and their contours
12 in binary images. The main step of this algorithm is to use a contour tracing technique to
13 detect the external contour and possible internal contours of each component, and also to
14 identify and label the interior area of each component. Labeling is done in a single pass over
15 the image, while contour points are revisited more than once, but no more than a constant
16 number of times. Moreover, no re-labeling is required throughout the entire process, as it is
17 required by other algorithms. Experimentation on various types of images (characters, half-
18 tone pictures, photographs, newspaper, etc.) shows that our method outperforms methods
19 that use the equivalence technique. Our algorithm not only labels components but also ex-
20 tracts component contours and sequential orders of contour points, which can be useful for
21 many applications.

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23 *Keywords:* Component-labeling algorithm; Contour tracing; Linear-time algorithm

24 1. Introduction

25 Researchers often face the need to detect and classify objects in images. Techni-
26 cally, image objects are formed out of components that in turn are made of

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27 connected pixels. It is thus most equitable to first detect components from images.
28 When objects have been successfully extracted from their backgrounds, they also
29 need to be specifically identified. For the latter purpose, component contour is of-
30 ten a useful resource for identifying objects. There are methods that identify ob-
31 jects from either chain codes [5] or Fourier descriptors [12], which are derived
32 from object contours. There are also methods that match object contours against
33 certain stochastic models [9]. These methods demonstrate that both component
34 and contour labeling is an effective method for detecting and identifying two-
35 dimensional objects.

36 In this paper, we present a method that simultaneously labels contours and
37 components in binary images. This method is applicable in areas in which we
38 must detect components and also classify them by means of certain contour fea-
39 tures. Document analysis and recognition (DAR) in particular is an area for
40 which our method is beneficial. High-order objects, such as half-tone pictures,
41 characters, textlines, and text regions, need to be classified in order to effectively
42 perform DAR [1]. Components are the basic ingredients of all high-order ob-
43 jects. Labeling components is therefore a commonly used technique for extract-
44 ing high-order objects. The objective of DAR is not simply to extract high-order
45 objects, but to recognize individual characters found within textual areas. There
46 are many methods that employ certain contour features for classifying characters
47 [2,10,16].

48 Our method labels each component using a contour tracing technique. This
49 method is based on the principle that a component is fully determined by its con-
50 tours, just as a polygon is fully determined by its vertices. This method also pro-
51 vides a procedure for finding all component pixels. We scan an image the same
52 way as it would be encountered by a scanner, i.e., from top to bottom and from
53 left to right per each line. When an external or internal contour is encountered,
54 we use a contour-tracing procedure [6] to complete the contour and assign a label,
55 say L , to all pixels on the contour. When the contour is traced back to its starting
56 point, we resume scanning at that point. Later on, when the contour pixels labeled
57 L are visited again, we assign the same label L to black pixels that lie next to
58 them.

59 Our method has the following advantages. First, it requires only one pass over the
60 image. Contour points are visited more than once due to the aforementioned contour
61 tracing procedure, however no more than a constant number of times. Second, it
62 does not require any re-labeling mechanism. Once a labeling index is assigned to a
63 pixel, its value is unchanged. Third, we obtain as by-products all contours and se-
64 quential orders of contour pixels. Fourth, experimental results show that our algo-
65 rithm is faster than traditional component-labeling algorithms.

66 Our paper is organized as follows. A review of five traditional component-la-
67 beling algorithms is given in Section 2. The details of our method are described
68 in Section 3. Analysis and proof of our algorithm are provided in Section 4.
69 The experimental results of our method as compared with the five algorithms
70 from Section 2 are discussed in Section 5. A brief conclusion is given in Sec-
71 tion 6.

72 2. Review of traditional component-labeling algorithms

73 In this section, we review five important methods for component labeling. One
74 of them is the first proposed method, and the other four use varied strategies in
75 attempt to improve on the first. They all attempt to re-label component pixels ac-
76 cording to an equivalence relation induced by 8-connectivity. The first method pro-
77 posed by Rosenfeld and Pfaltz [13] performs two passes over a binary image. Each
78 point is encountered once in the first pass. At each black pixel P , a further exam-
79 ination of its four neighboring points (left, upper left, top, and upper right) is con-
80 ducted. If none of these neighbors carries a label, P is assigned a new label.
81 Otherwise, those labels carried by neighbors of P are said to be equivalent. In this
82 case, the label of P is replaced by the minimal equivalent label. For this purpose, a
83 pair of arrays is generated, one containing all current labels and the other the
84 minimal equivalent labels of those current labels. In the second pass, label
85 replacements are made.

86 Haralick [8] designed a method to remove the extra storage required for the pair
87 of arrays proposed in the first method. Initially, each black pixel is given a unique
88 label. The labeled image is then processed iteratively in two directions. In the first
89 pass, conducted from the top down, each labeled point is reassigned the smallest
90 label among its four neighboring points. The second pass is similar to the first, ex-
91 cept that it is conducted from the bottom up. The process goes on iteratively until
92 no more labels change. The memory storage of this method is small, but the
93 overall processing time varies according to the complexity of the image being
94 processed.

95 The method proposed by Lumia et al. [11] compromises between the two previous
96 methods. In the first top-down pass, labels are assigned to black pixels as in the first
97 method. At the end of each scan line, however, the labels on this line are changed to
98 their minimal equivalent labels. The second pass begins from the bottom and works
99 similarly as the top-down pass. It can be proved that all components obtain a unique
100 label after these two passes.

101 Fiorio and Gustedt [4] employ a special version of the union-find algorithm [15] in
102 that it runs in linear time for the component-labeling problem (see also Dillencourt
103 et al. [3]). This method consists of two passes. In the first pass, each set of equivalent
104 labels is represented as a tree. In the second pass, a re-labeling procedure is per-
105 formed. The operation used in the union-find technique serves to merge two trees
106 into a single tree when a node in one tree bears an 8-connectivity relationship to a
107 node in the other tree.

108 The method proposed by Shima et al. [14] is particularly suitable for compressed
109 images in which a pre-processing procedure is required to transform image elements
110 into runs. A searching step and a propagation step are exercised iteratively on the
111 run data. In the searching step, the image is encountered until an unlabeled run (re-
112 ferred to as focal run) is found and is assigned a new label. In the propagation step,
113 the label of each focal run is propagated to contiguous runs above or below the scan
114 line.

115 3. Our method

116 In our method, we scan a binary image from top to bottom and from left to right
 117 per each line. We first provide an overview of this method as follows. Conceptually,
 118 we can divide the operations into four major steps that are illustrated in Figs. 1A–D.

119 In Fig. 1A, when an external contour point, say A , is encountered the first time, we
 120 make a complete trace of the contour until we return to A . We assign a label to A and
 121 to all points of that contour.

122 In Fig. 1B, when a labeled external contour point A' is encountered, we follow the
 123 scan line to find all subsequent black pixels (if they exist) and assign them the same
 124 label as A' .

125 In Fig. 1C, when an internal counter point, say B , is encountered the first time, we
 126 assign B the same label as the external contour of the same component. We then
 127 trace the internal contour containing B and also assign to all contour points the same
 128 label as B .

129 In Fig. 1D, when a labeled internal contour point, say B' , is encountered, we fol-
 130 low the scan line to find all subsequent black pixels (if they exist) and assign them the
 131 same label as B' .

132 In the above procedure, we only make a single pass over the image and assign to
 133 each component point either a new label or the same label as the point preceding it
 134 on the scan line. The details of this algorithm are given below.

135 For simplicity, we assume that the pixels in the uppermost row are all white (if
 136 they are not, we add a dummy row of white pixels). For a given document image
 137 I , we associate with I an accompanying image L , which stores the label information.
 138 Initially, all points of L are set to 0 (i.e., they are *unlabeled*). We then start to scan I
 139 to find a black pixel. Let C be the label index for components. Initially, C is set to 1.
 140 The aforementioned four conceptual steps can be reduced to three logical steps.
 141 The first step deals with a newly encountered external point and all points of that
 142 contour, the second step a newly encountered internal point and all points of that
 143 contour, and the third step all black pixels not dealt in the first two steps.

144 Let P be the current point that is being dealt by our algorithm.

145 *Step 1:* If P is unlabeled and the pixel above it is a white pixel (Fig. 2), P must be
 146 on an external contour of a newly encountered component. So we assign label C to
 147 P , meanwhile execute *contour tracing* (a contour tracing procedure whose details will

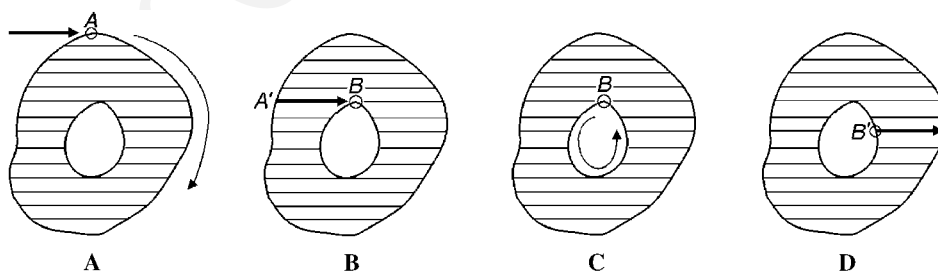


Fig. 1. The four major steps in tracing and labeling component points.

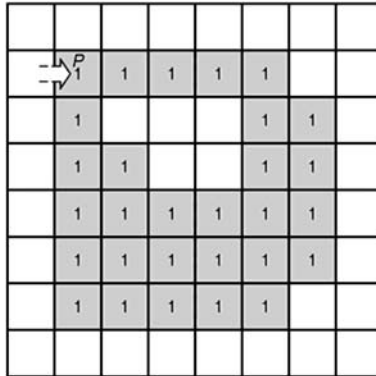


Fig. 2. P is the starting point of an external contour. 1, unlabeled black pixels.

148 be given later) to find that external contour, and assign label C to all the contour pixels.
 149 els. We then increase the value of C by 1.

150 *Step 2:* If the pixel below P is an *unmarked* white pixel (the meaning of ‘unmarked’
 151 will be given in a moment), P must be on a newly encountered internal contour.
 152 There are two possibilities. First, P is already labeled (Fig. 3A). In this case, P is also
 153 an external contour pixel. Second, P is unlabeled (Fig. 3B). In this case, the preceding
 154 point N on the scan line (the left neighbor of P) must be labeled. We then assign P
 155 the same label as N . In either case, we proceed to execute *contour tracing* to find the
 156 internal contour containing P , and assign the same label to all the contour pixels.

157 *Step 3:* If P is not a point dealt in Step 1 or Step 2 (i.e., P is not a contour point),
 158 then the left neighbor N of P must be a labeled pixel (Fig. 4). We assign P the same
 159 label as N .

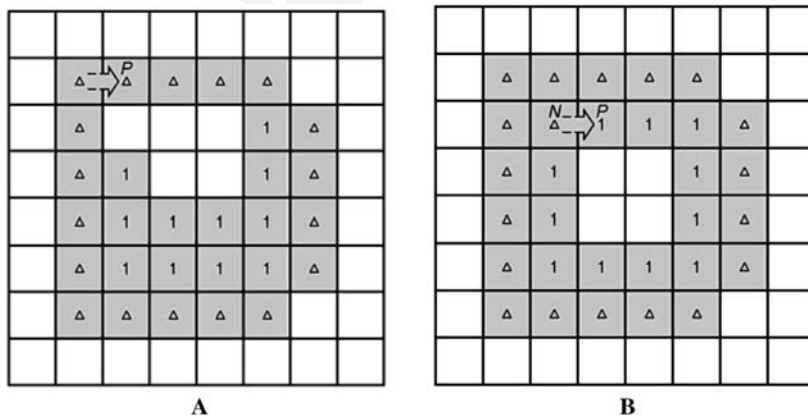


Fig. 3. (A) P is the starting point of an internal contour. P also lies on an external contour. (b) P is the starting point of an internal contour, but it is not on an external contour. 1, unlabeled black pixels; Δ , labeled black pixels.

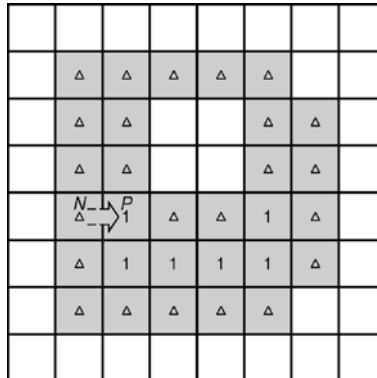


Fig. 4. P is an unlabeled point and its left neighbor N is already labeled. 1, unlabeled black pixels; Δ , labeled black pixels.

160 As is illustrated in Fig. 5, in order to avoid executing *Counter Tracing* at the point
 161 Q , we *mark* surrounding white pixels of a component with a negative integer. Thus,
 162 at the time the scan line sweeps Q , the pixel below Q is no longer an *unmarked* white
 163 pixel. On the other hand, the neighbor below a first encountered internal contour
 164 pixel P (Fig. 5) is still unmarked since the internal contour containing that pixel
 165 has not been traced yet.

166 By marking surrounding white pixels, we also ensure that each internal contour is
 167 traced only once. As illustrated in Fig. 6, when the internal contour has been traced,
 168 the neighbor below R is no longer an unmarked pixel and we thus avoid tracing the
 169 internal contour once again when R is encountered by the scan line (we need to trace the
 170 internal contour at a point only when the white pixel below that point is unmarked).

171 The operation of marking surrounding white pixels with a negative integer is
 172 included in the procedure *Tracer*, which is called forth by the procedure *contour trac-*
 173 *ing*. Both procedures will be described below.

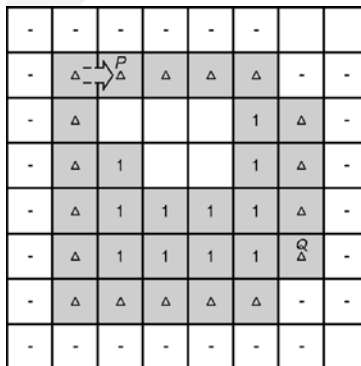


Fig. 5. Surrounding white pixels are marked with a native integer when a contour has been traced. 1, unlabeled black pixels; Δ , labeled black pixels; -, marked white pixels.

207 4. Complexity and efficacy

208 We first analyze the time complexity of our algorithm. The key lemma is as fol-
209 lows:

210 **Lemma 1.** *Our algorithm visits each pixel a constant number of times.*

211 **Proof.** Since the image is encountered only once, all non-contour pixels are visited
212 exactly once. On the other hand, the number of times *contour tracing* visits a pixel is
213 equal to the number of contours containing the pixel. A contour pixel can lie on at
214 most four contours (Fig. 10). Thus, our algorithm scans each non-contour pixel only
215 once and traces a contour pixel no more than four times. \square

216 Since each pixel, when visited, takes a constant amount of time for processing,
217 Lemma 1 immediately implies the following.

218 **Theorem 2.** *Our algorithm runs in linear time.*

219 We proceed to prove the efficacy of our algorithm. The contour tracing procedure
220 is a well-known technique whose proof can be found in Haig et al. [7]. The pixel on a
221 contour first encountered in the scanning process must be, due to the scanning direc-
222 tion, on the leftmost point on the uppermost row of that contour. We refer to this
223 point as the *opening pixel* of the contour. Moreover, the opening pixel of the external
224 contour of a component is also called the *opening pixel* of that component. Note that
225 our algorithm ensures that each component is first encountered at its opening pixel
226 and each contour is traced from its opening pixel.

227 It is also clear that all black pixels are labeled with a certain index by our algo-
228 rithm. To prove the correctness of our algorithm, we need to show that all pixels

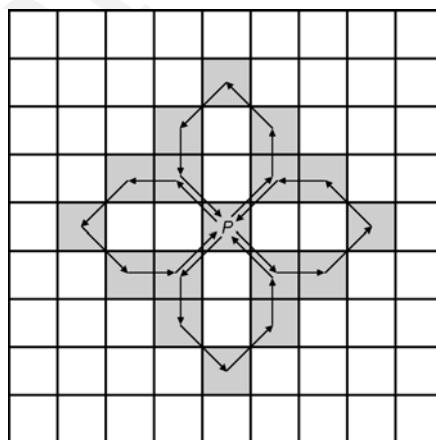


Fig. 10. An example in which a contour pixel P lies on four contours.

229 of the same component are assigned the same label and that all pixels of different
 230 components are assigned different labels.

231 **Lemma 3.** *All pixels in the same component are assigned the same label.*

232 **Proof.** Suppose that the opening pixel of the component is labeled C . According to
 233 Step 1 of our algorithm, all pixels on that external contour are also labeled C . To prove
 234 that all the remaining pixels of the same component are assigned the same label, we
 235 apply induction in the same order as they are encountered by the scan line. Suppose
 236 that the current pixel encountered is P . We assume that any component pixel en-
 237 countered before P is labeled C . We then have to show that P is also labeled C . As-
 238 suming, without loss of generality, that P is *not* an external contour point (we already
 239 know that external contour pixels are labeled C), we consider the following three cases.

240 *Case 1:* P is not on any internal contour. In this case, P must be an interior point
 241 since P is not an external contour point either. It follows that the left neighbor Q of P
 242 is a black pixel. Since Q is encountered before P , Q is labeled C by our inductive hy-
 243 pothesis. So P is also labeled C , according to Step 3 of our algorithm.

244 *Case 2:* P is on an internal contour Ψ but P is not the opening pixel of Ψ . Let Q be
 245 the opening pixel of Ψ . Q must be encountered before P , by the definition of an open-
 246 ing pixel. Q is labeled C by our inductive hypothesis. It follows that P is assigned the
 247 same label as Q , according to Step 2 of our algorithm. Thus, the label of P is C .

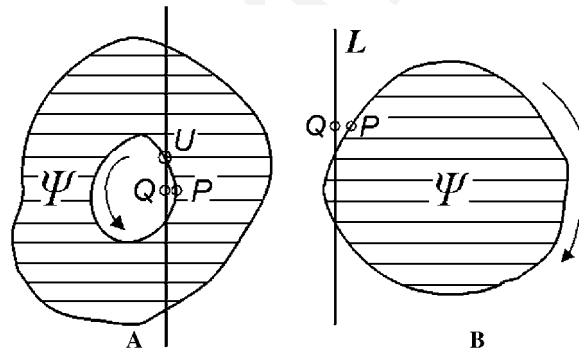


Fig. 11. (A) If P lies on an internal contour Ψ and its left neighbor Q is a white pixel, then Ψ contains a point U lying above Q . (B) Otherwise, the vertical line L that passes Q does not intersect with Ψ above Q . This implies that Q lies outside the component containing P , and that P is an external contour point.

Table 1
 Six types of methods, including ours, that are being compared

A	Rosenfeld et al.
B	Haralick [8]
C	Lumia et al. [11]
D	Fiorio et al.
E	Shima et al. [14]
F	Our method

248 *Case 3:* P is the opening pixel of any internal contour containing P . In this case, the
 249 left neighbor Q of P is a black pixel for the following reason: if Q is a white pixel, P must
 250 lie on some internal contour Ψ , and Ψ contains a pixel U that lies on a row above Q
 251 (Fig. 11A) and also above P . This contradicts the fact that P is an opening pixel. We
 252 thus prove that Q is a black pixel. Since Q is encountered before P , Q is labeled C by
 253 our inductive hypothesis. P is thus labeled C , according to Step 2 of our algorithm.
 254 In either case, P is labeled C , which completes our inductive step. \square

255 **Lemma 4.** *Pixels in different components are assigned different labels.*

256 **Proof.** From the previous lemma, all pixels in a component are assigned the same
 257 label as the opening pixel of the component. On the other hand, Step 1 of our al-
 258 gorithm ensures that the opening pixel of a component is assigned a new label. So,
 259 different components get different labels. \square

Table 2
Performances of the six methods being compared

Document type	Image size (M pixels)	#CC	Methods					
			A	B	C	D	E	F
Average processing time (s)								
Legacy documents	2.16	741	0.50	0.41	0.70	0.10	0.07	0.06
	4.33	1668	1.95	1.02	1.21	0.19	0.15	0.13
	8.69	3708	7.03	3.27	4.08	0.38	0.30	0.27
	17.39	6570	29.95	6.54	8.08	0.74	0.55	0.49
Headlines	2.16	439	0.70	0.79	0.76	0.12	0.10	0.07
	4.33	916	2.35	1.79	1.56	0.24	0.19	0.14
	8.69	1577	7.48	3.91	3.31	0.47	0.37	0.30
	17.39	3145	39.20	9.20	6.11	0.89	0.71	0.58
Textual content	2.16	1808	1.78	1.02	0.76	0.12	0.12	0.08
	4.33	3509	6.45	2.50	1.53	0.23	0.24	0.15
	8.69	6825	25.29	6.30	3.10	0.47	0.45	0.31
	17.39	13,157	370.71	15.31	7.37	0.92	0.92	0.66
Halftone pictures	2.16	14,823	3.18	3.86	2.77	0.18	0.19	0.09
	4.33	28,793	14.51	10.09	5.08	0.37	0.42	0.19
	8.69	52,087	59.57	25.76	13.05	0.71	0.75	0.36
	17.39	131,628	773.93	100.83	28.13	1.41	1.68	0.76
Newspaper	2.16	1408	1.65	1.08	0.83	0.12	0.11	0.07
	4.33	4828	6.61	3.51	4.20	0.24	0.24	0.15
	8.69	12,024	25.99	7.94	5.05	0.51	0.52	0.32
	17.39	16,680	287.31	17.24	21.10	0.98	0.93	0.67
Photographs	1.92	4196	2.18	4.49	2.02	0.16	0.15	0.09
	3.14	2018	1.72	2.88	2.54	0.23	0.18	0.11
	3.87	3206	3.22	3.13	5.78	0.26	0.20	0.13
	4.91	1416	2.41	2.75	2.96	0.35	0.25	0.15

#CC, number of connected components.

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260 The following theorem is a consequence of Lemmas 3 and 4.

261 **Theorem 5.** *Our algorithm produces a correct labeling for the components.*

262 5. Experimental results

263 Our methods are compared with the five other component-labeling methods dis-
 264 cussed in Section 2. We use six types of test images: legacy documents, headlines, tex-
 265 tual contents, half-tone pictures, newspaper, and photographs. The test environment
 266 is an Intel Pentium III 1 GHz personal computer with 384MB SDRAM. Each doc-
 267 ument type has four sets of images. Each set, in turn, consists of four images whose
 268 sizes correspond to four paper sizes: A3, A4, A5, and A6.

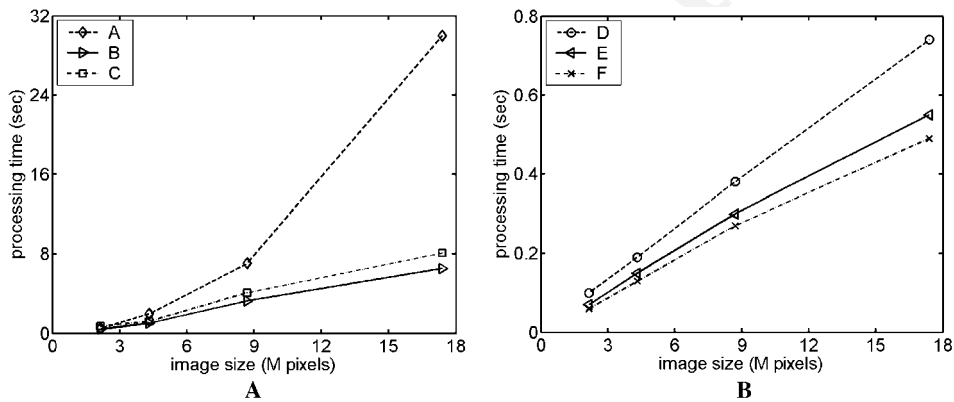


Fig. 12. Performances of the six methods for legacy documents.

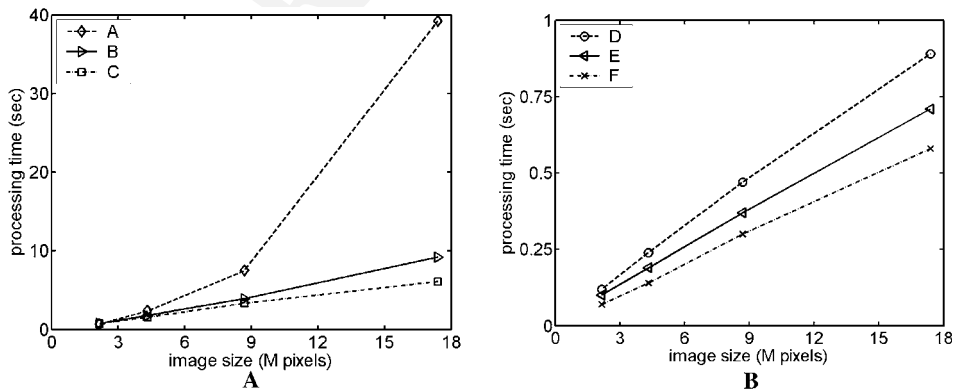


Fig. 13. Performances of the six methods for headlines.

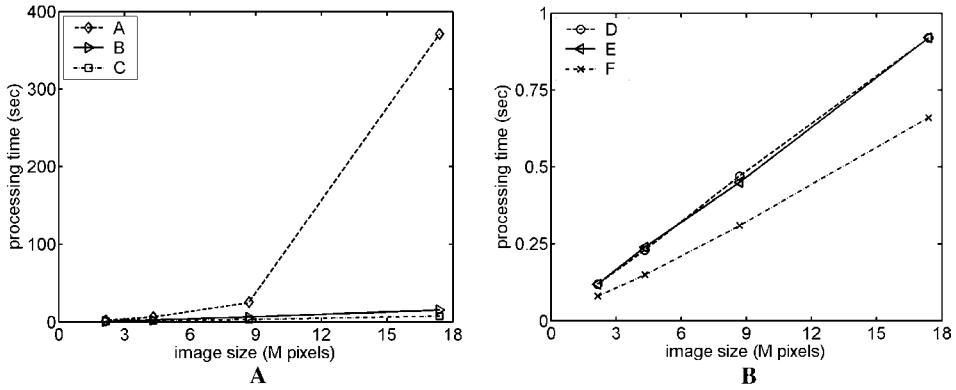


Fig. 14. Performances of the six methods for textual contents.

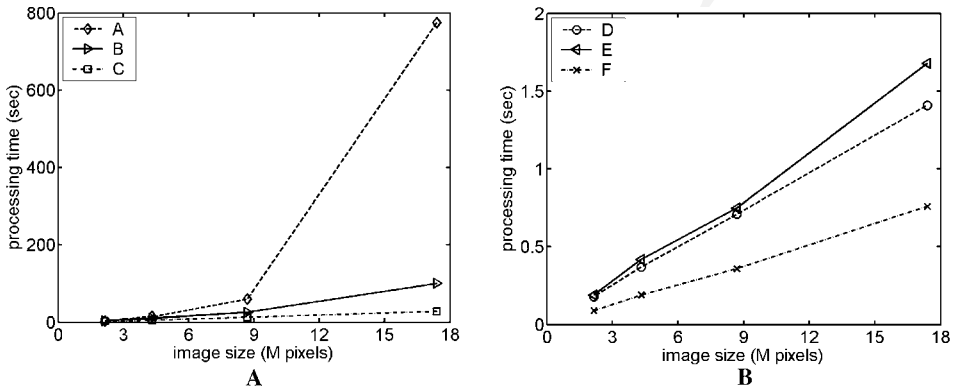


Fig. 15. Performances of the six methods for half-tone pictures.

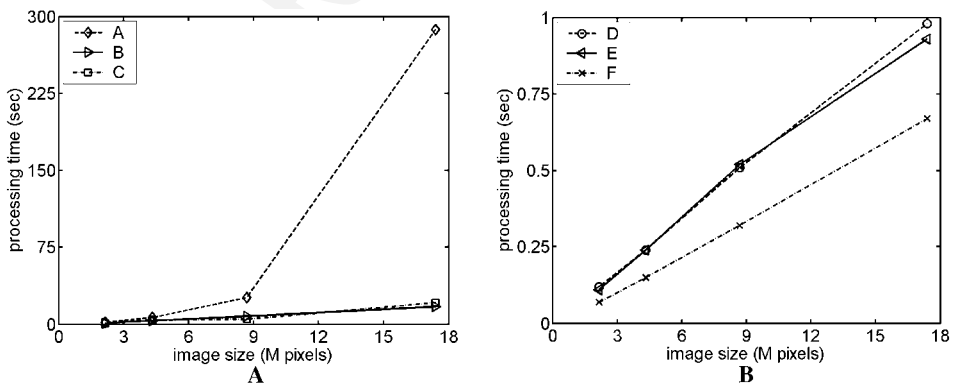


Fig. 16. Performances of the six methods for newspaper.

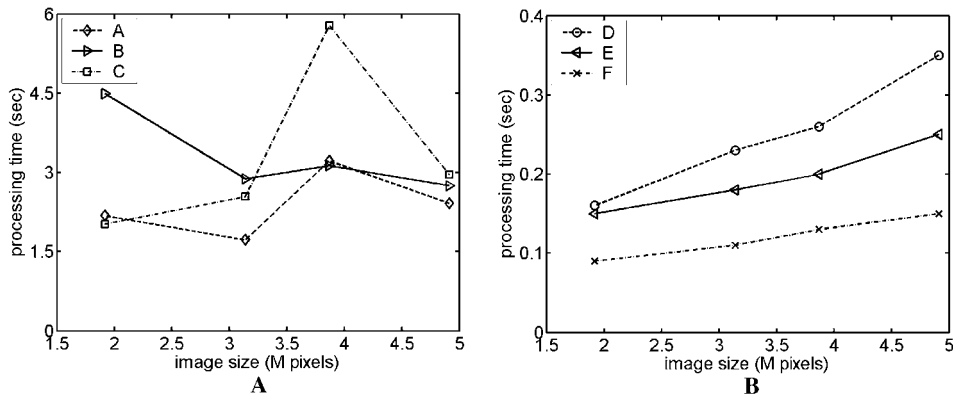


Fig. 17. Performances of the six methods for photographs.

269 We have to make certain test images by cutting relevant objects from various
 270 sources and pasting them onto a blank canvas of a specified size. The reason we need
 271 to make a collage out of small images is because we are not able to obtain a docu-
 272 ment that consists of only a single type of specified objects (e.g., headlines). Some test
 273 images, however, can be directly segmented from their sources (e.g., photographs,
 274 newspaper, and legacy documents) without being made into collages. All six algo-
 275 rithms being compared are listed in Table 1. The comparison results are listed in Ta-
 276 ble 2. The performances of all the algorithms are shown in Figs. 12–17. In these
 277 figures, the size of the test image is plotted along the horizontal axis, and the average
 278 processing time of each method is plotted along the vertical axis.

279 6. Conclusion

280 We have presented a new component-labeling algorithm that employs contour
 281 tracing technique. This method scans a binary image only once and traces each con-
 282 tour pixel no more than a constant number of times. It is thus computationally ef-
 283 fective in labeling connected components and also finding all contours and
 284 sequential orders of contour pixels. In experiments on six types of images of various
 285 sizes, we compare our method with five other algorithms. The results show that our
 286 algorithm outperforms all of them in terms of computational speed.

287 References

- 288 [1] F. Chang, Retrieving information from document images: problems and solutions, *Internat. J.*
 289 *Document Anal. Recogn., Special Issues Document Anal. Office Syst.* 4 (2001) 46–55.
 290 [2] F. Chang, Y.C. Lu, T. Pavlidis, Feature analysis using line sweep thinning algorithm, *IEEE Trans.*
 291 *Pattern Anal. Mach. Intell.* 21 (1999) 145–158.
 292 [3] M.B. Dillencourt, H. Samet, M. Tamminen, A general approach to connected-component labeling for
 293 arbitrary image representations, *J. Assoc. Comput. Mach.* 39 (1992) 253–280.

- 294 [4] C. Fiorio, J. Gustedt, Two linear time Union-Find strategies for image processing, *Theor. Comput.*
295 *Sci.* 154 (1996) 165–181.
- 296 [5] H. Freeman, Techniques for the digital computer analysis of chain-encoded arbitrary plane curves,
297 *Proc. Natl. Electron. Conf.* (1961) 421–432.
- 298 [6] T.D. Haig, Y. Attikiouzel, An improved algorithm for border following of binary images, *IEE Eur.*
299 *Conf. Circuit Theory Design* (1989) 118–122.
- 300 [7] T.D. Haig, Y. Attikiouzel, M.D. Alder, Border following: new definition gives improved borders, *IEE*
301 *Proc.-I* 139 (1992) 206–211.
- 302 [8] R.H. Haralick, Some neighborhood operations, in: M. Onoe, K. Preston, A. Rosenfeld (Eds.), *Real*
303 *Time/Parallel Computing Image Analysis*, Plenum Press, New York, 1981.
- 304 [9] Y. He, A. Kundu, 2-D shape classification using hidden Markov model, *IEEE Trans. Pattern Anal.*
305 *Mach. Intell.* 13 (1991) 1172–1184.
- 306 [10] A.K. Jain, R.P.W. Duin, J. Mao, Statistical pattern recognition: a review, *IEEE Trans. Pattern Anal.*
307 *Mach. Intell.* 22 (2000) 4–37.
- 308 [11] R. Lumia, L. Shapiro, O. Zuniga, A new connected components algorithm for virtual memory
309 computers, *Comput. Vision Graphics Image Process.* 22 (1983) 287–300.
- 310 [12] E. Persoon, K.S. Fu, Shape discriminations using fourier descriptors, *IEEE Trans. Syst. Man*
311 *Cybernet.* 7 (1977) 170–179.
- 312 [13] A. Rosenfeld, P. Pfaltz, Sequential operations in digital picture processing, *J. Assoc. Comput. Mach.*
313 12 (1966) 471–494.
- 314 [14] Y. Shima, T. Murakami, M. Koga, H. Yashiro, H. Fujisawa, A high speed algorithm for
315 propagation-type labeling based on block sorting of runs in binary images, *Proc. 10th Internat. Conf.*
316 *Pattern Recogn.* (1990) 655–658.
- 317 [15] R.E. Tarjan, Efficiency of a good but not linear set union algorithm, *J. Assoc. Comput. Mach.* 22
318 (1975) 215–225.
- 319 [16] O.D. Trier, A.K. Jain, T. Taxt, Feature extraction methods for character recognition—a survey,
320 *Pattern Recogn.* 29 (1996) 641–662.