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PREPROCESSING AND PRESORTING OF ENVELOPE IMAGES FOR AUTOMATIC SORTING USING OCR

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Abstract—This paper reports a review and feasibility study undertaken to investigate methods of preprocessing envelope images to (i) extract the address block from the image in the presence of other data, and (ii) presort the addresses into sub-classes suitable for recognition by an OCR system with separate recognition channels for machine and handwritten address classes. Results are reported from an analysis of over 1500 actual address images of different print and writing styles obtained using existing OCR sorting equipment. These results show a correct address block location rate of around 98%, and that presorting of addresses into machine printed or hand printed/written was around 86% correct. Sorting in terms of OCR machine readable or not OCR machine readable (as defined by existing OCR equipment) was around 70% correct.

Preprocessing Postal sorting Binary images Optical character recognition
Printed addresses Handwritten addresses

1. INTRODUCTION

Although many papers on the subject of OCR for postal addresses have been published, until recently very few considered address recognition as other than a character recognition problem. Where the context of the address was considered at all, it was used primarily as a method of improving the accuracy of the character recognition itself, by using post-processing to apply world knowledge which constrains the choice of valid characters.[1,2] This strategy was satisfactory with first generation postal OCR systems since these were invariably used principally to sort bulk mailings where both the style of printed address and the layout of the envelope were known in advance.

The next generation of systems however will have to cope with input envelopes which are much less constrained. Available statistics suggest that between 20–30% of mail is handwritten or hand printed with the remainder being typewritten, printed by data processing systems, or duplicated.[3,4] Future systems will therefore need to handle hand printed and handwritten addresses, upper case and mixed case typed addresses and machine printed addresses, with both proportional and fixed pitch printing. Furthermore, envelopes may contain other information such as postmarks, stamps, return addresses, company logos and stickers, any of which may be confused with the address. In severe cases, this unwanted material may even overlap the required address.

In the general case, a whole variety of address location, segmentation and recognition problems may be encountered, each of which may represent a demanding pattern recognition problem in its own right. In this paper, we first review these areas and discuss reasonable simplifications which can be made to present a more tractable problem, and then develop an empirical approach and present sample results illustrating its performance.

2. A TAXONOMY OF THE ADDRESS RECOGNITION PROBLEM

In this section we review the various problems that may occur in attempting to locate and read the address block (and in particular any zipcode or postcode it may contain). The taxonomy of problems is necessarily presented sequentially, and for the most part may be viewed as a hierarchical set of problems which can be tackled in a top-down manner, but this is not the only approach nor is it necessarily the best. Alternatives proposed among the papers reviewed below include a blackboard-based approach and iterative methods. The sequential presentation here does, however, emphasise the extent to which the general address recognition problem for unconstrained mailpieces exceeds the complexity of OCR of addresses as implemented in current commercial mail sorting systems.

2.1. *Envelope characteristics*

2.1.1. *Physical characteristics.* In addition to conventional sizes of envelopes for letter post, business and advertising mail uses a wide variety of larger envelopes up to A4 or even A3 format. Many advertising mailshots contain extensive graphic material in addition to the address on the envelope face. With larger envelopes in particular, there is little standardisation in the positioning of the address block. For an A4 size envelope, an image several thousand pixels in size along each axis may be required in order to resolve the address characters adequately for OCR at any position on the envelope face: images of this size will inevitably require high computational power and/or parallelism to process in real time. If newspapers and magazines sent by post are also to be recognised, even more severe problems may be encountered, especially where the item is packaged in clear plastic, allowing the underlying print to show through.

Mail items of this complexity have been considered by some researchers.[5-12] In general however, where solutions have been implemented, performance is not yet adequate for commercial application either in speed or accuracy of address block location.

2.1.2. *Image characteristics.* Mailpieces are typically scanned using cameras or linear CCD scanning systems, to produce either a colour or grey-scale image. Infra-red and ultra-violet imaging have also been used in some cases.[6,7] In later stages of the processing, the image is typically reduced to a binary image format, by carrying out adaptive thresholding.

2.1.3. *Simplifying assumptions.* In our own experimental work, reported below, we were constrained to work with binary images generated directly by the scanner section of an AEG printed mail OCR system. The mechanical configuration of the scanner confined investigation to conventional size envelopes (9″ × 4.5″ or smaller), with address blocks located in the bottom two-thirds of the envelope face. Simple mechanical sorting can be used to preselect envelopes matching these size constraints. Mail matching this format undoubtedly is less variable in layout than larger items, hence subsequent address block location is easier, while remaining a realistic incremental objective in developing less constrained address recognition systems.

2.2. *Address block location*

In the case of totally unconstrained mailpieces, expert systems and AI techniques have been proposed as methods of identifying the address block in the presence of other text and graphic clutter on the envelope.[7,9-11] Other work (e.g. Bergman *et al.*[12]) has concentrated upon extracting simpler geometrical and topological features to identify the address block. Ultimately these two approaches converge: if the complexity of the rule-base used to identify the address block is sufficient, an expert system represents the embedded rules more elegantly, and is easier to construct; however, any rule-base still requires the extraction of a variety of low-level geometrical features to which the rules can be applied.

We confined our experimental work to the examination of simple geometrical features of the envelope image, to establish whether such features were by themselves sufficient to identify the address block accurately in images derived purely from conventional-sized envelopes.

2.3. *Machine print and handwriting*

It is probable that different character recognition techniques will be needed for handwritten and machine printed classes of addresses. This requirement is most efficiently handled if all envelopes are preprocessed to categorise them into separate classes, which can then be handled in parallel recognition channels using algorithms optimised for each class, for example statistical algorithms for machine printed addresses and structural algorithms for handwritten addresses. Current machine print OCR systems already use parallel recognition channels optimised for upper case and lower case characters and numerals[13] to increase throughput and performance.

In our experimental work, we have investigated possible gross features of the address block which could be used to distinguish between printed and handwritten classes of address. Further features might also be used to distinguish upper case from mixed case text. This problem does not seem to have been given prominence in other researchers work, though it is mentioned by Antognini and Turnbaugh[9] and by Srihari *et al.*[14]

2.4. *Zipcode/postcode location and segmentation*

Most researchers have based their high-level address recognition strategy primarily upon recognition of a numeric zipcode or alphanumeric postcode, supplemented by verification of the address deduced from this code using the remainder of the address block information. Hence the next problem is to locate and distinguish the zipcode or postcode from the other components of the address. In our own work,[2,15] we have assumed that the postcode is written within boxes printed on the envelope, to eliminate the problem of parsing the address block to locate zipcode/postcode. Other research has not imposed this constraint,[16-19] and in general uses an empirical strategy of searching for the zipcode/postcode by scanning from bottom-right to top-left. This approach relaxes the constraints on address writing, but increases significantly the complexity of the recognition process.

2.5. *Character recognition*

In contrast to printed character recognition, recognition of hand print and handwriting has concentrated on syntactic and structural character recognition techniques, suggesting that any final composite print and handwriting address recognition system will require a number of different parallel OCR channels to which different types of address will be directed.

Analysis of sample unconstrained handwritten addresses, as part of the work reported below, suggests that character and word segmentation within a handwritten address will present major technical problems for some time to come. Where solutions have been proposed[16–20] they rely upon heuristic techniques applied through complex expert system rule-bases combined with iteration, so that if subsequent character recognition fails to produce decisions with high confidence, the word is resegmented and reapplied to the character recognition system. Even if adequate accuracy can be achieved by these systems, real-time operation remains a difficult problem. A possible simplifying assumption[2,15] is that, as a minimum, the postcode will be written within constrained character boxes.

2.6. *Postprocessing of zipcode/postcode data*

It is generally accepted that high performance handwritten character recognition in off-line applications can only be achieved by the use of higher level syntactic and contextual knowledge. Work in our research group[15] has shown that the application of a combination of postcode syntax rules and contextual knowledge derived from a dictionary of postcodes can more than double the overall postcode recognition rate. The postcode/zipcode is verified by determining the address which corresponds to the postulated postcode using a database, and then comparing sample features of this address with features extracted from the remaining words in the address.[17,18,21]

2.7. *Hardware techniques for real-time systems*

Commercial printed mail OCR systems such as those manufactured by AEG already use multiple processors based upon bit-slice microprocessor technology and configured as pipelined, parallel systems, to achieve processing rates of up to 10 mailpieces per second. Since OCR systems for unconstrained handwritten addresses require many additional pattern recognition problems to be resolved over and above those tackled for printed mail, it is likely that commercial real-time implementations will in turn require substantially more processing power. The order of magnitude processing requirement is indicated by research at the Department of Computer Science, SUNY, Buffalo,[6,8,17] where a full address block location system (ABLS) is reported as requiring on average 10 minutes/mailpiece running time on a Sun 3 single processor workstation.[6] Hence a performance improvement of roughly 10^4 is required to achieve a throughput comparable with current printed OCR systems.

Several researchers have reviewed architectures for real-time processing of unconstrained mail piece images, including coarse-grained hypercubes, shared memory parallel processors and fine-grained real-time image processing cards,[8] toroidal meshes[22] and hierarchical trees.[23] Less conventional approaches such as neural networks, digital signal processors and ASIC's,[24] and hybrid optical/digital systems[15,25] have also been suggested. As yet, however, the speed improvements achieved in practical experiments using these architectures fall at least two orders of magnitude short of what would be required for commercial applications.

Bass[24] has noted the exceptional recognition performance requirements which arise from tackling the unconstrained address recognition problem. If a six stage hierarchical processing pipeline (corresponding broadly to the sequence of sections 2.1–2.6) is used, and an overall requirement for 95% correct sorting assumed, this implies a need for 99.3% accuracy at each stage of the pipeline, and 99.95% accuracy in recognising individual characters. (Uniform performance is assumed for each stage.) This calculation provides convincing evidence of the need for separate modules to interact with each other to reduce module performance level requirements where possible (for example by exploiting redundancy in character recognition).

2.8. *Practical applications*

In view of the extensive problems associated with unconstrained recognition of handwritten addresses, it is likely that further mechanization in postal address sorting will occur as an evolutionary process, gradually adding features and capabilities to current commercial systems as these are re-engineered to exploit new generations of computer technology. Depending upon the speed at which the various problems outlined above are resolved, this may result in the development of two alternative strategies for computerised mail sorting.

2.8.1. *Presorting.* If solutions to the problems of address block location, zpicode/postcode location and handwritten character recognition can be found, preprocessing of the mailpiece image will be used to separate handwritten from printed address blocks, and direct each to the appropriate recognition module.

2.8.2. *Culling.* A less technically demanding extrapolation from existing capabilities is to add preprocessing capabilities to existing printed mail OCR systems to enable them to be used efficiently with mixed mail input. This requires the development of a culling system which is capable of rejecting all mail items except those containing (recognisable) printed addresses, using simple features extracted from the mailpiece image. The culler may also provide other aspects of preprocessing, such as address block location. To be cost effective, a culler must be capable of fully loading the input to the OCR system; depending on mail mix this may for example require mailpieces to be processed at twice the speed of the OCR system itself. The role of culling in the sorting of live mail is illustrated in Fig. 1.

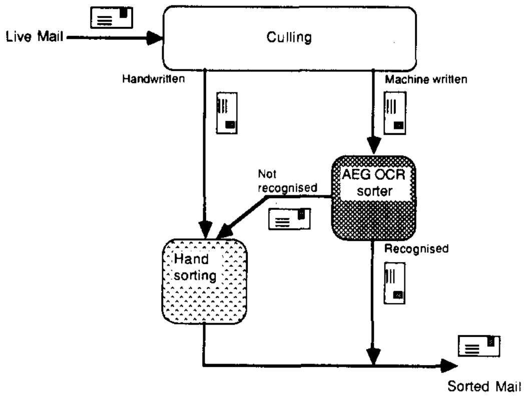


Fig. 1. The role of culling in live mail sorting.

In our experimental work, reported below, we distinguish presorting and culling performance as two separate aspects which are worthy of investigation.

3. PREPROCESSING AND PRESORTING OF STANDARD SIZE ENVELOPES

3.1. *General requirements*

Intuitively, it should be possible to achieve the required presorting by making certain global feature measurements of the address without the need to read or recognise individual characters. To minimise computation, preprocessing should be performed on a low-resolution image rather than the full pixel image (2048 × 512 pixels in our case) generated by the scanner. The use of this approach is supported by the fact that human readers can identify the address block region in the presence of other regions when the image is composed of bounding rectangles representing characters, stamps, and other information,[5] that is, without any knowledge of the actual characters.

3.2. *Address region identification*

Address block identification from an envelope image is in many ways a similar problem to document segmentation: the initial aim therefore is to segment the full envelope image into a number of regions and then to select the address block region using simple criteria. Figure 2 shows a typical example envelope bit-image, from which it can be seen that if regions are identified using standard 4-connected or 8-connected rules at pixel level, each region within the address area will correspond to approximately a character, whereas in practice what is required is a lower resolution region consisting of the address as a whole.

A low-level technique which can be used to link characters and lines to form a single address region is run-length smoothing (or smearing).[26] The principle of this technique is that if a row of binary pixels exist in either horizontal or vertical axes the runs of white pixels between black pixels are converted to black if the run is less than a certain length (the smearing value). This technique seems particularly appropriate in this application because, by choosing a suitable horizontal smearing value, characters and words of the address can be grouped together into single regions, while by choosing a suitable vertical smearing value, lines of the address can be grouped together. Thus it would seem possible to use this technique not only to find the extent of the address region on an envelope, but also to identify sub-regions such as lines, words and characters and their position within the address region. Furthermore, the use of vertical and horizontal smearing emphasises the vertical and horizontal structural characteristics of the address, while ignoring any unwanted diagonally close elements of the envelope image. A simple horizontal and vertical smearing algorithm was therefore used in this feasibility study.

Assuming that the envelope image can be subdivided into a number of major regions using this technique, the next problem is to decide which of these regions constitutes the address. Srihari *et al.*[27] and Yet *et al.*[5] discuss two approaches, based upon simulated annealing and the use of a rule-based system respectively, by which a global best match allocation of labels to regions can be achieved. Other researchers also seem to favour the use of knowledge-based systems to tackle this problem,[7,9-11] but the advantages may be as much in expediting experimental work as in the performance achieved. Both of these approaches are relatively computationally intensive, thus in our feasibility study we chose simply to label the address region as being that region which was nearest to the expected address position on the envelope.

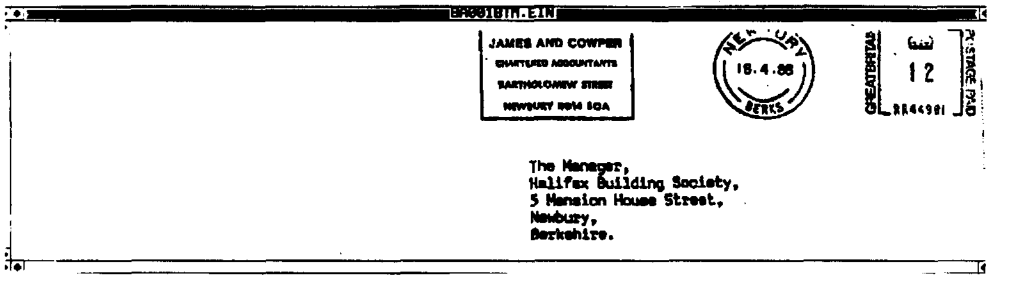


Fig. 2. Example envelope bit-image (shown at half true resolution in each axis).

3.3. *Address classification*

Wahl *et al.*[26] discuss a number of possible measures for discriminating text blocks within a document, but their general requirement is to discriminate printed text from graphics or image data. In this case, the primary requirement is to discriminate between machine printed and handwritten text, which requires a different set of features to be extracted. After studying a small set of randomly chosen envelope images, the following features were selected for further investigation:

(i) *Contour regularity*: the contour of the address region appeared to be more regular in machine printed addresses than in handwritten addresses, because of the tendency of printed addresses to be horizontally and vertically aligned and the higher consistency of letter sizes.

(ii) *Pixel density*: the pixel density within the address region appeared to be higher for machine printed addresses than for handwritten addresses, because the character and line spacings for machine printed addresses were generally denser than for handwritten addresses.

(iii) *Address regularity*: machine printed addresses were generally more regularly spaced, both horizontally and vertically, than handwritten addresses (particularly for fixed pitched typing).

4. ADDRESS REGION LOCATION

The technique we chose to implement is based on extracting the single most likely address region in the image using pixel densities, region shape and region location as the selection criteria. Parameters for the various algorithms used in the address region location process were optimised heuristically for printed addresses in this feasibility study, with the initial intention of producing a system which would accurately identify machine printed addresses and reject all others (i.e. for application as a culler rather than a presorter).

The original image (Fig. 2) was first smeared horizontally to accentuate regions of high pixel density as shown in Fig. 3. The horizontal smearing value in the full resolution image was 40 pixels or 0.2″. This value was chosen because it was the widest typical word spacing observed in machine printed addresses and would therefore join most words in each address line without joining surrounding non-address regions such as the postmark or logo unless they were within 0.2″ either side of the address. For application in a presorting system, where the intention is to identify the address region accurately in handwritten and hand printed addresses as well as printed addresses, an adaptive technique for optimising smearing width and height would be required. This is discussed in Section 7.

The resolution of the image was reduced from 2048×512 pixels to 256×64 pixels by subsampling the smeared image in 8×8 pixel blocks and setting each block in a separate array to either black or white depending upon the pixel density within the block (see Fig. 4). The reason for doing this was to reduce later processing. By scanning the smeared image, the threshold for deciding whether a block should be black or white could be high due to the accentuated number of black pixels in a legitimate printed region of this image. This had the desirable effect of filtering out small noisy regions which were unlikely candidates for the address region. By experimentation on a small set of images it was concluded that a black/white decision threshold of 30 black pixels in each 64 pixel block produced the desired performance. The disadvantage of having such a high threshold is that the top, bottom and sides of the address block may be clipped by up to one block or eight pixels. This corresponds to 0.04″ which is approximately one third of a 12 point character. Whilst this amount of clipping is unlikely to cause problems in address classification it would cause problems in address recognition and would therefore need to be compensated for once the address region has been located if character recognition is to be attempted.

Each set of 8-connected black blocks in the low resolution image were next grouped together as a region. For each of these regions a number of features were extracted. These were:

(a) Coordinates of the region's bounding rectangle in the full resolution image (x_{min}, y_{min} and x_{max}, y_{max});

(b) Aspect ratio ($x_{max} - x_{min}/y_{max} - y_{min}$) for the region;

(c) Density of black pixels in the smeared full resolution image region;

(d) Density of black pixels in the original full resolution image region.

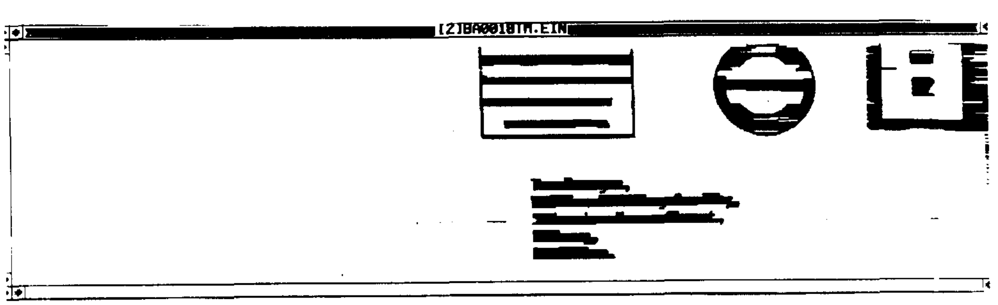


Fig. 3. Image of Fig. 2 after horizontal smearing.

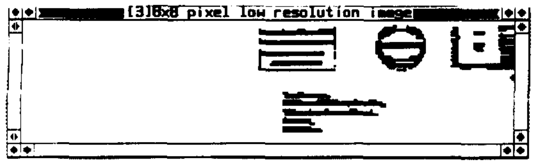


Fig. 4. Image of Fig. 3 after resolution reduction of 8 × in each axis.

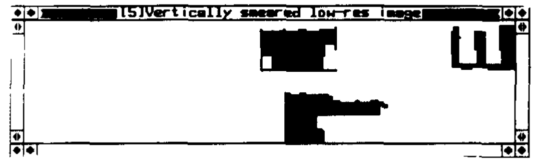


Fig. 6. Image of Fig. 5 after vertical smearing.

These features were then used to eliminate regions which could not feasibly be part of an address. Regions to be retained should be single lines or words in the address as smearing will have joined most letters and words together in machine printed addresses. Therefore all regions which:

(a) were only one block in height, or

(b) had an aspect ratio (x/y) less than 1 or greater than 70, or

(c) had an area of less than 4 blocks

were deleted.

In addition, the pixel density within an address region in the original image is usually at least 0.2, and at least 0.4 in the smeared image if the region contains machine printed characters. Therefore all regions which:

(a) had a pixel density in the original image of less than 0.1, or

(b) had a pixel density in the smeared image of less than 0.3

were deleted, to reject any region with a density too low to represent print.

Removal of all regions not meeting these threshold criteria further reduced subsequent processing requirements, and resulted in the image shown in Fig. 5.

A further smearing operation was next performed vertically in order to join the lines of the address together whilst keeping all other surrounding regions separate. The vertical smearing value in the low resolution image was chosen as 6 blocks or 0.24″. This value was chosen such that it was large enough to merge lines of the address together without joining them to other non-address regions. The value roughly corresponds to the spacing between double spaced 10 point characters. Figure 6 shows the resulting image after this operation. Again, each set of 8-connected black blocks in the low resolution image were grouped together as a region. These new regions are referred to as major regions and the previous set as sub-regions.

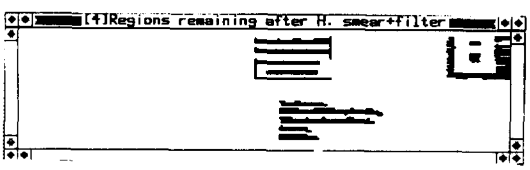


Fig. 5. Image of Fig. 4 after eliminating non-viable address regions.

The list of major regions extracted from the vertically smeared low resolution image include within their enclosed area all sub-regions existing before the image was smeared vertically. Sub-regions are therefore correlated with a major region if the sub-region is wholly enclosed within the major region. The result of this operation is to leave a set of major regions and associated sub-regions which, in a machine printed address, will ideally consist of the full address block as the major region and the lines of the address as the corresponding subregions.

After correlating all major regions and sub-regions there may be only a single major region and its associated sub-regions, but more commonly a number of major regions (and their associated sub-regions) will exist, one of which will be the address. The method of selecting which major region is the most likely candidate for the address is based on removing all unlikely shaped major regions and then selecting the single major region from those remaining which is most central to the scanned image.

The decision as to whether a major region can feasibly be an address was based solely on its shape. All major regions and their associated subregions were removed if

(a) they were less than 100 pixels in width, or

(b) they were less than 48 pixels in height, or

(c) they had an x/y aspect ratio of greater than 35.

The final single major region selection was based on a distance measure from a nominal central point $C = (x_c, y_c)$ in the original image. The central point was chosen as half the horizontal length and one third the vertical height of the scanned image. The vertical height is fixed at 512 pixels and consequently the y_c coordinate was always 171, but the x_c coordinate varies up to a maximum of 1024 depending on the last coordinate in the digitised image. Figure 7 shows the final major region and its associated sub-regions.

The distance from central point C to a major region was selected as a weighted $D4$ or 'city block' distance (Gonzalez and Wintz,[28] p. 32) which weights the distance to favour the nearest major block along the x-axis from C rather than the y-axis. This is based on the assumption that the address will usually be around the centre of the scanned envelope towards the bottom. The most frequently observed blocks which should be avoided are the stamp and associated postmark in the top right corner and other extraneous information such as a company logo which is usually observed in the bottom or top left hand corners.

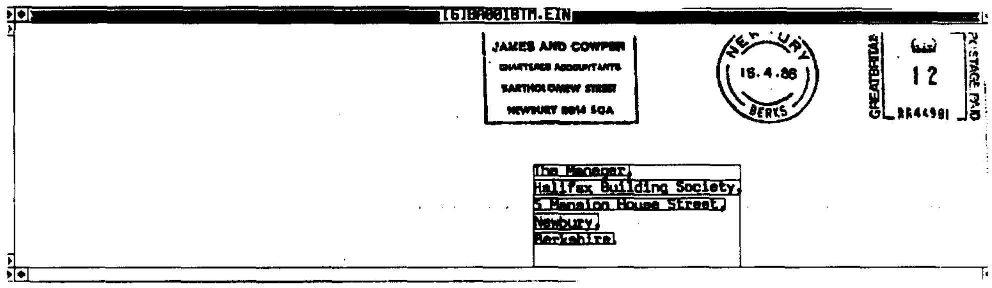


Fig. 7. Full envelope bit-image showing remaining major and sub-regions.

The $D4$ distance between two points $A = (x, y)$ and $B = (p, q)$ was weighted to favour the x-axis as:

$$D4(A, B) = |x - p| + 2^*|y - q|.$$

The distance to each region was calculated for the nearest point on the boundary of the region to point A if point A was outside the region and $D4(A, B) = 0$ if A was inside the region. The region with the smallest value of $D4$ was then selected as the address region; if two regions had the same D4 value, then the larger of the two regions was selected.

5. ADDRESS CLASSIFICATION

A set of global features were extracted from the located address region to classify the address into channels for handwritten or machine printed addresses. The measures selected were based on the regularity of the contour of the final major address region in the horizontally and vertically smeared low resolution image, the density of black pixels in the final major address region in the original and horizontally smeared full resolution image and the regularity of peaks (corresponding to character spacing) in the vertical histogram of the final major region in the original full resolution image. Seven features were chosen as possible candidates for discriminating between printed and handwritten addresses. These were:

(i) two features based upon measurements of contour regularity;

(ii) three features based upon measurements of pixel density;

(iii) two features based upon measurements of character distribution regularity within the address region.

These features were selected empirically from observation of the global characteristics of the major address region located in a set of 30 address images of various types selected at random from our database of address images. The feature measurements are described in more detail below. No attempt has yet been made to optimise the definition of these features.

5.1. *Contour regularity*

Contour regularity was measured by calculating the number of corners in the regions contour and also the contour length. The technique used to calculate the contour length used a contour following algorithm proposed by Rosenfeld (see Ballard and Brown,[29] p. 144). The contour length was calculated as the summation of all distances between neighbouring boundary pixels. A length of 1 was used if the boundary pixels were 4-connected and a length of $\sqrt{2}$ used if the boundary pixel was one of the four additional 8-connected pixels. The number of corners in the contour was also counted during this contour tracing operation.

Using this information, two measures were made on the address region:

Measure A: 100 * Contour length/(No. of corners * bounding rectangle length);

Measure B: Bounding rectangle length/No. of corners.

5.2. *Pixel density*

The black pixel densities for the subregions were already available in the lists of subregions previously extracted and therefore did not need recomputing. Three measures were taken using the black pixel densities for the subregions. These were:

Measure C: sum of all black pixel densities in the sub-regions of the original images address region.

Measure D: sum of all black pixel densities in the sub-regions of the smeared images address region.

Measure E: sum of measure C and measure D.

5.3. *Character distribution regularity*

The regularity of distribution of characters within the address region was measured using a Discrete Fourier Transform (DFT), with the aim of identifying characteristic spectra peaks corresponding to the line and character spacing of fixed pitch printed addresses. To reduce computation, rather than calculating a 2-D transform, vertical and horizontal histograms of the address region were calculated and 1-D transforms taken of these histograms. In practice, initial experiments revealed that only the horizontal DFT produced a discriminable feature (corresponding to the character spacing), so all subsequent analysis was carried out on this data alone. Discrete Fourier spectra components corresponding to feasible ranges of character spacings (5–25 characters per inch) were evaluated, and the peak value identified within this range, giving measure F. A more restrictive allowed character range was then applied (9–13 characters per inch), yielding measure G.

6. RESULTS

The results presented are in three parts. Firstly, the address block location algorithm was evaluated by visual inspection using an initial set of 332 address images of various types. These results are presented in section 6.2. Secondly, the pre-sorting features were evaluated initially on a database of 962 address images (a superset of the 332 images used in section 6.2), and later on a further set of 587 address images for which the OCR readability using existing AEG equipment installed in a Post Office sorting office was known. The results of this evaluation are presented in sections 6.4–6.6. Finally, the character regularity measure was evaluated on the later set of 587 address images. This feature was considered separately since its primary use would be to distinguish fixed pitch print from all other classes, and therefore it would not be suitable alone as a discriminator between printed and handwritten addresses. Results are presented in section 6.7.

6.1. *Data sets*

Experimental work was carried out using two separate sets of sample address images. Data set 1 consisted of a total of 962 sample envelope images extracted from live mail, in the following proportions:

40.5% handwritten mixed case addresses;
29.1% handwritten upper case addresses;
12.4% machine printed mixed case addresses;
18.0% machine printed upper case addresses.

From this, a subset (data set 1A) of 332 images was extracted for the experimental work on address block location, comprising all the printed addresses and a sample of 20 addresses each from the handwritten mixed case and handwritten upper case addresses.

Data set 2 was chosen to provide a larger sample of printed addresses, evenly distributed between upper case, mixed case, fixed pitch and proportionally spaced addresses. Data set 2 comprised a total of 587 sample envelope images of which 229 (39.0%) were readable and 358 (61.0%) were not readable by the AEG OCR equipment. This distinction between OCR readable and not OCR readable allowed the sorting performance between machine readable and not machine readable addresses to be determined in a later stage of our evaluation (see section 6.6). (It should be noted that the printed addresses were deliberately chosen to present difficult character recognition problems to the AEG equipment, so that roughly equal numbers of readable and non-readable addresses were obtained, and do not represent the address recognition performance to be expected in normal use of this equipment.)

These addresses were subdivided into six classes of printing styles in the proportions shown in Table 1.

Data set 2 was subdivided into two roughly equal sized parts keeping similar proportions of the six address classes in each part. Data set 2A (comprising 287 address images) was used as a training set for optimising the choice of feature thresholds; data set 2B (comprising 300 address images of which 119 were OCR readable and 181 were not OCR readable) was used as a test set.

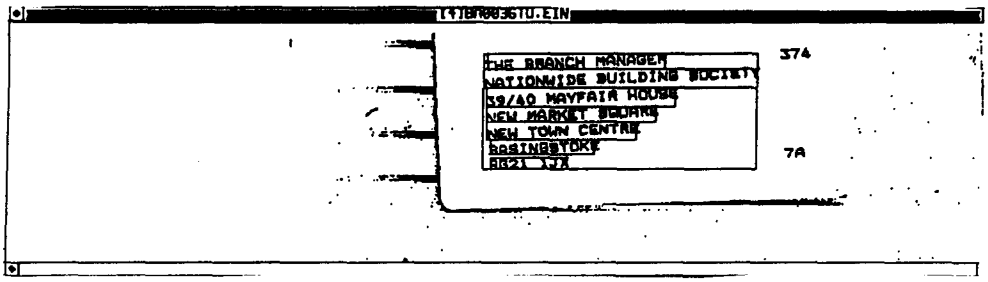
6.2. *Address block location*

Because of the choice of threshold values, the address location algorithm was strongly biased to locate the address region correctly if it was machine printed. To test its performance, it was evaluated on data set 1A, which comprised 119 envelope images containing an upper case only machine printed address, 173 envelope images containing a mixed case machine printed address, and 40 envelope images containing a handwritten or handprinted address (20 of each).

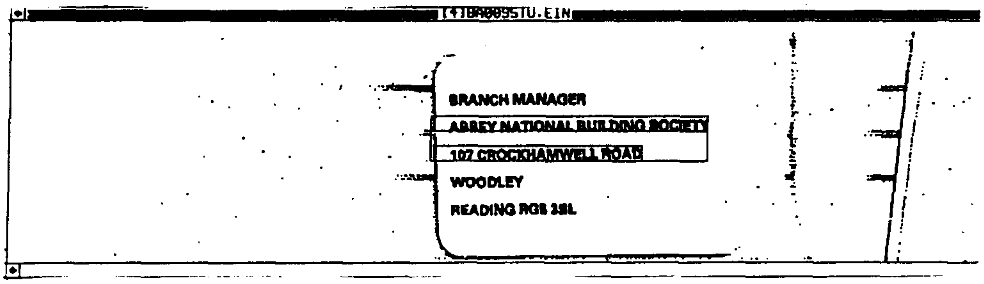
Out of the 119 images of machine printed upper case addresses 113 (95%) addresses were accurately located, five had part of the address missing from the address region selected and one missed the true address region completely. Figure 8 shows a typical example of an address which is fully and correctly located, an address which is only partly located and the case where the address region was missed completely. Where part of the address was not included within the selected address block, this was generally due to encountering line spacings greater than the vertical smearing height chosen, combined in some cases with interference from other image features which had been combined with the address by vertical smearing. The one address region which was totally missed occurred because a handwritten annotation (probably added during the postal sorting process due to an error in the original postcode) was placed immediately adjacent to the address region itself. Both regions were correctly isolated but the final region selection algorithm in this case chose the

Table 1

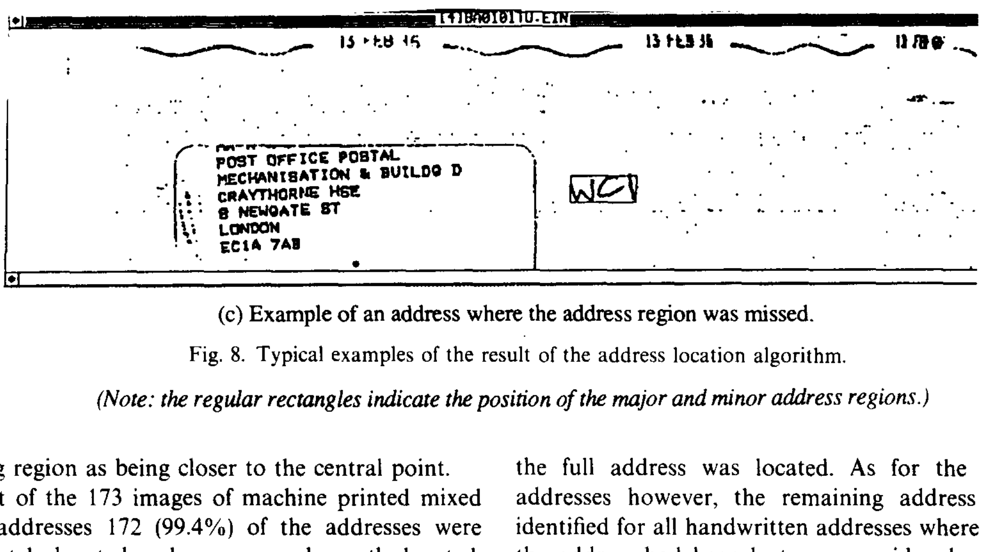
	Readable by AEG equipment	Not readable by AEG equipment
Handwritten mixed case (including cursive) addresses	0.0%	16.4%
Hand printed upper case addresses	0.0%	15.3%
Machine printed, fixed pitch, upper case addresses	8.9%	7.8%
Machine printed, fixed pitch, mixed case addresses	9.5%	7.7%
Machine printed, proportionally spaced, upper case addresses	12.3%	5.1%
Machine printed, proportionally spaced, mixed case addresses	8.3%	8.7%



(a) Example of an image where all the address region was located.



(b) Example of an address where only part of the address region was located.



(c) Example of an address where the address region was missed.

Fig. 8. Typical examples of the result of the address location algorithm.

(Note: the regular rectangles indicate the position of the major and minor address regions.)

wrong region as being closer to the central point.

Out of the 173 images of machine printed mixed case addresses 172 (99.4%) of the addresses were accurately located and one was only partly located, for the same reason as outlined above.

In all cases where part of the address was lost there still remained a significant amount of the address which was considered sufficient for classification purposes. Only one address was missed completely out of the 292 machine printed addresses analysed, representing a correct location rate of 99.7%.

Only a small representative sample of randomly chosen handwritten and hand printed envelope images was analysed. In all 40 cases, the address was at least partially located, but in 32 of these cases, some words or lines of the address were omitted due to line and word spacings being too large to be smeared together by the smearing processes. Figure 9 shows two examples of handwritten addresses which were not fully located. In the remaining eight cases, the full address was located. As for the printed addresses however, the remaining address region identified for all handwritten addresses where part of the address had been lost was considered sufficient for classification purposes.

6.3. *Presorting strategies*

The choice of the feature thresholds used in classifying between printed and handwritten addresses can be viewed in three ways. Firstly, they could be optimised to maximise the correct classification between handwritten and machine written addresses. This effectively assumes a symmetric sorting system, where both handwritten and machine printed addresses are sorted in separate channels, with equal costs attributable to each. We define this classification as *presorting*, and results for this are presented in section 6.4.

Secondly, the feature thresholds could be optimised to make best use of an existing printed address OCR

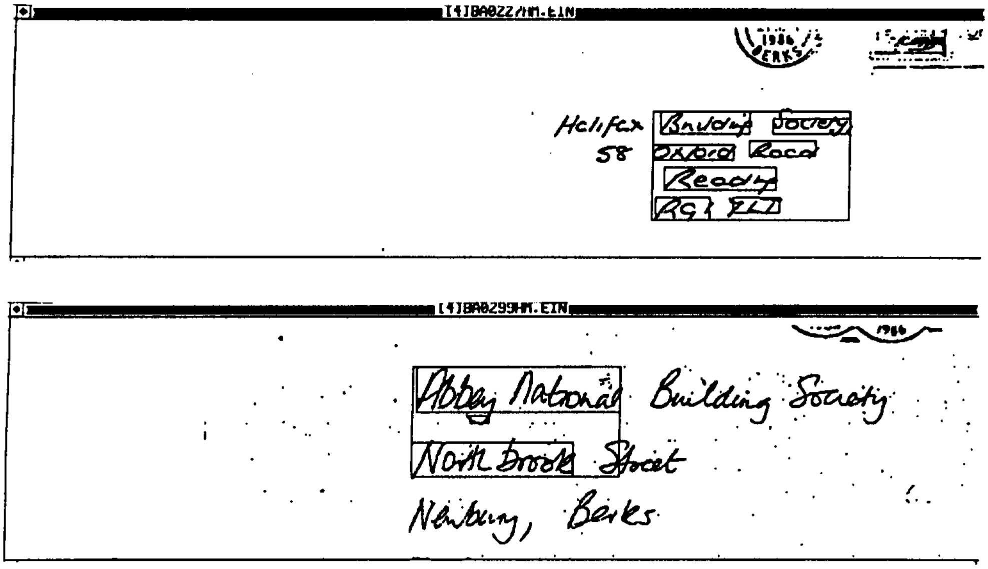


Fig. 9. Two examples of handwritten addresses where the address region was only partly located. *(Note: the regular rectangles indicate the position of the major and minor address regions.)*

sorting system, where the handwritten channel is sorted manually (an asymmetric sorting system—see Fig. 1). As a result of the unequal costs of sorting in the two channels, different thresholds may be needed to minimise total costs. We define this type of classification as *culling*, and present results based upon suitable threshold choices in section 6.5.

Thirdly, the feature thresholds could be optimised to give the best overall classification with respect to machine readable and non-machine readable classes. This classification differs from the first, because in a practical system, some machine printed addresses may not in practice be machine readable (and possibly a few handwritten addresses will be machine readable). For data set 2, it was known whether each address was machine readable or not, hence thresholds could be optimised against this criterion. Results for this case are presented in section 6.6.

6.4. *Presorting performance*

Histogram distributions of each of the five contour regularity and pixel density features were plotted for each type of address. Approximately optimal threshold choices were made from the histograms for each feature to maximise correct classification for that feature into the two classes printed and handwritten, using the full set of images in data set 1 as the training set. These thresholds produced the classifications shown in Table 2. From these results it appears that feature B produced the highest overall correct classification, but that features D and E, though slightly less satisfactory overall, gave the most accurate classification performance for handwritten and printed addresses respectively.

The effect of combining various groups of these features was also investigated: in this case classification was based upon a simple majority vote among the constituent features for each group. The following example groups were chosen:

(i) combined performance using all five measures;

(ii) combined performance of measures A, B and E;

(iii) combined performance of measures B, D and E.

Table 2. Classification performance with data set 1, with feature thresholds chosen to optimise presorting performance

	% correct classification				Mean % overall correct classification (weighted)
	Hand-written mixed case	Hand printed upper case	Machine printed mixed case	Machine printed upper case	
Measure A	90.3	85.4	72.7	64.7	82.1
Measure B	95.4	91.4	81.6	89.9	91.5
Measure C	96.2	91.1	51.4	71.4	84.7
Measure D	99.0	88.9	68.2	81.5	89.1
Measure E	79.7	55.4	96.0	91.6	76.8
All 5 measures	97.7	92.9	72.3	86.6	91.2
Measures A, B, E	94.9	88.6	80.2	88.2	90.0
Measures B, D, E	97.9	85.0	91.3	90.8	92.0

As can be seen the overall correct classification performance, weighted by the number of images in each class, was in all cases around 90%. These results were considered encouraging, although the data set was not balanced between classes, and the results were achieved using the same set of data for threshold selection and performance assessment.

6.5. *Culling performance*

A reasonable assumption in designing a culling system is that the cost of machine sorting will (ultimately) be substantially less than the cost of hand sorting. It follows from this that a culling system should be set up to minimise the amount of printed mail erroneously sent to the hand sorting channel (see Fig. 1), even if the choice of feature threshold to achieve this results in a significant proportion of the handwritten mail being sent to the OCR channel. (We assume that this mail would subsequently be rejected by the OCR system and redirected to the hand sorting channel, resulting only in a reduction in throughput of the OCR system). Feature thresholds should thus be chosen to maximise the correct classification of machine written addresses.

Culling performance was assessed using data set 2B. Optimised thresholds for each of the five features were chosen using data set 2A so that 90% correct classification of machine printed addresses was achieved. In selecting these thresholds it became apparent that achieving >90% correct classification for machine written addresses meant that correct handwritten address classification would be as low as 50% in some cases.

The results for each of the individual measures for each type of address image analysed are summarised in Table 3. As can be seen, Measures A and C produced a large number of misclassifications when dealing with handwritten/printed addresses, and measures B and D were the most accurate overall. Applying the three voting schemes in this case produced little further improvement as compared with measures B and D alone, with voting between measures A, B and E producing marginally the best overall performance of 88.7% correct classification. Figure 10 illustrates a typical address image which was correctly classified as machine printed and one which was incorrectly classified as not machine printed. As can be seen the image which was incorrectly classified was, in fact, unreadable.

6.6. *Machine readable vs non-machine readable performance*

There are four possible outcomes to the automatic culling process as shown in Fig. 11.

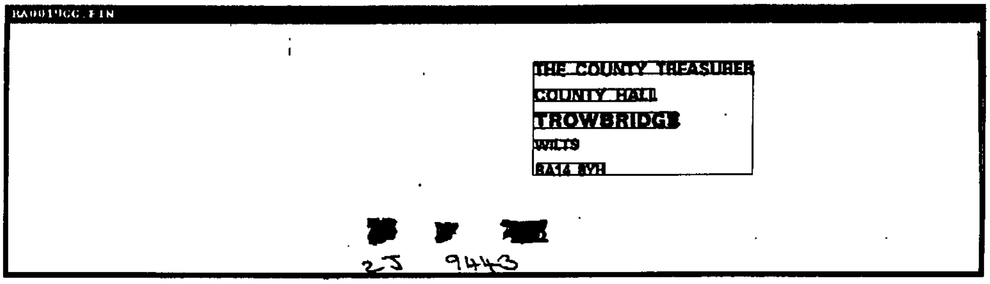
Addresses can be classified correctly as machine readable or unreadable, or classified incorrectly as machine readable or unreadable. Thresholds were chosen for the five features using data set 2A such that 90% correct classification of machine readable images was achieved on data set 2A. Using these thresholds the culling performance was assessed on data set 2B; this produced the results shown in Table 4.

From the results shown in Table 4 it can be seen that between 81.5% and 86.6% of machine readable addresses were correctly passed as machine readable by each individual measure. This increased only slightly to between 84% and 87.7% when voting was applied. Addresses which were not machine readable were correctly classified less accurately at between 39.8% and 64.1% for individual measures and between 54.7% and 64.1% when voting was applied. Thus with voting applied between 35.9% and 45.3% of the mail which is not machine readable would be passed as OCR readable. At the sme time between 12.6% and 16.0% of the OCR readable mail would be wrongly passed for hand sorting. Figure 12 illustrates an example of an address which was OCR readable and an example of one which was not OCR readable. From these images it is apparent that it is not always easy to discriminate between machine readable and not machine readable without first attempting to read the address.

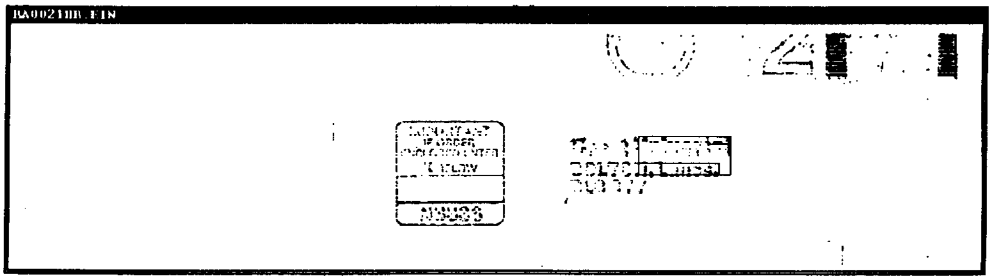
The mean overall correct classification percentages are given for comparison with Tables 2 and 3, but should be treated with care, since they are based upon address samples chosen specifically to provide roughly equal numbers in all classes: as a result, an unrealistically high proportion of printed addresses are included which are not readable by the OCR system.

Table 3. Classification performance using data set 2B with feature thresholds chosen to optimise culling performance

	% correct classification						
	Hand-written mixed case	Hand printed upper case	Machine printed upper case fixed pitch	Machine printed mixed case fixed pitch	Machine printed upper case prop. spaced	Machine printed mixed case prop. spaced	Mean % overall correct classification
Measure A	56.3	60.0	95.9	91.2	86.3	86.0	80.0
Measure B	85.4	80.0	89.8	84.2	92.2	94.0	87.7
Measure C	66.7	48.9	83.7	66.7	92.2	98.0	76.3
Measure D	97.9	68.9	89.8	73.7	92.2	94.0	86.0
Measure E	89.6	64.4	87.8	70.2	92.2	96.0	83.3
All 5 measures	97.9	66.7	93.9	78.9	92.2	96.0	87.7
Measures A, B, E	87.5	73.3	95.9	86.0	92.2	96.0	88.7
Measures B, D, E	97.9	68.9	89.8	73.7	92.2	96.0	86.3



(a) Correctly classified as a machine printed address.



(b) Incorrectly classified as a handwritten address.

Fig. 10. Example of a correctly and an incorrectly classified address based on features optimised for culling performance (results based on voting using all five measures).

(Note: the regular rectangles indicate the position of the major and minor address regions.)

A more detailed analysis was also carried out by breaking down the results into the six distinct groups of handwritten and printed addresses comprising data set 2. This showed that the handwritten and hand printed addresses were correctly sorted as not machine readable in over 97% of cases. In contrast, machine printed mixed case proportionally spaced addresses were the type most frequently passed incorrectly as machine readable (approximately 46% were incorrectly sorted), and machine printed mixed case fixed pitch addresses were the type most frequently passed incorrectly as not machine readable (approximately 27% were incorrectly sorted). This illustrates clearly that the features chosen provided good performance in rejecting handwritten and handprinted addresses which are obviously not machine readable. They were much less effective, however, at distinguishing those printed addresses which proved to be machine readable from those which did not.

6.7. *Character regularity*

The character regularity feature would be used to discriminate between fixed pitch addresses and all other addresses, whether proportionally-spaced printed or handwritten: it might therefore be used as a second preprocessing stage after initial classification according to the measures above. Thus, in Table 5, 'correct classification' refers to classification into the two classes 'fixed pitch print' and 'others'. Classification error vs feature threshold graphs were plotted for each type of address format using the full set of images in data set 2. Approximately

Table 4. Classification performance using data set 2B, with feature thresholds optimised for machine readable vs not machine readable sorting

	% correctly sorted as machine readable	% correctly sorted as not machine readable	Mean % overall correct classification (weighted)
Measure A	81.5	39.8	56.3
Measure B	82.4	55.2	66.0
Measure C	86.6	57.5	69.0
Measure D	84.9	63.5	72.0
Measure E	82.4	64.1	71.3
All 5 measures	87.4	63.5	73.0
Measures A, B, E	85.7	54.7	67.0
Measures B, D, E	84.0	64.1	72.0

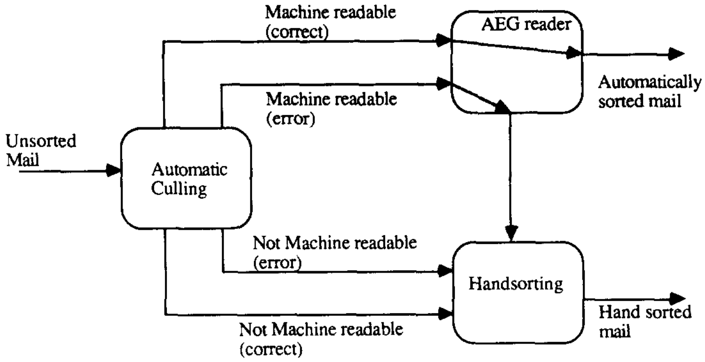
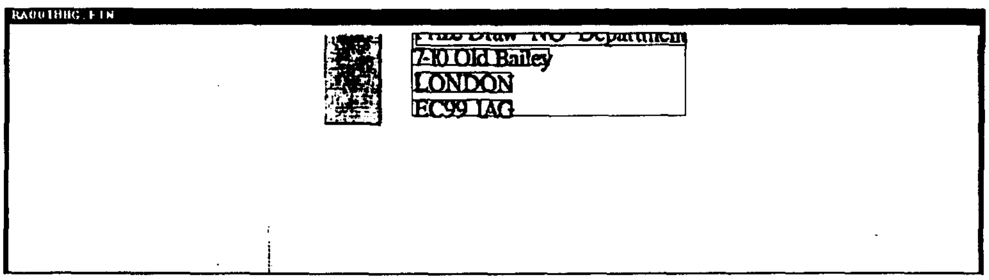
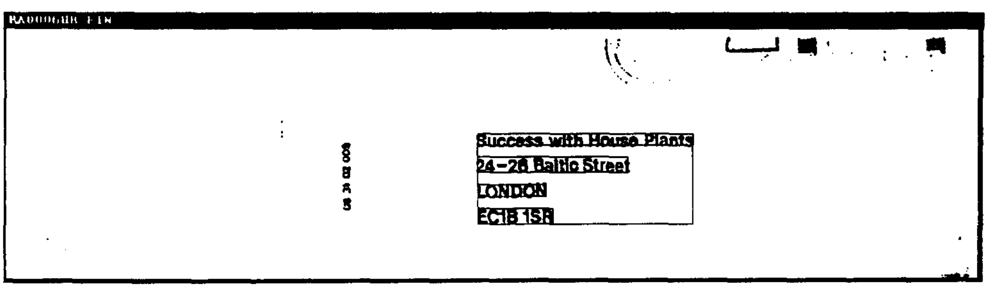


Fig. 11. The four possible outcomes of the culling process on unsorted mail.



(a) Correctly classified as machine readable.



(b) Incorrectly classified as machine readable.

Fig. 12. Examples of correctly and incorrectly classified addresses based on features optimised to distinguish between machine readable and not machine readable addresses (results based on voting using all five measures).

(Note: the regular rectangles indicate the position of the major and minor address regions.)

Table 5. Classification accuracy between fixed pitch printed addresses and 'others' using data set 2

	% correct classification						
	Hand-written mixed case	Hand printed upper case	Machine printed upper case fixed pitch	Machine printed mixed case fixed pitch	Machine printed upper case prop. spaced	Machine printed mixed case prop. spaced	Mean % overall correct classification
Measure F	75.3	82.2	70.2	95.7	72.0	86.7	80.4
Measure G	88.2	92.2	44.3	74.2	93.5	96.9	81.4

optimal threshold choices were made from the graphs for each of the two features F and G defined in section 5.3. These thresholds resulted in the classifications shown in Table 5. For both features, a classification accuracy of around 80% was achieved, but whereas feature F gave fairly consistent performance over all types of address, feature G gave improved classification accuracy for 'other' addresses, at the expense of reduced accuracy in classifying fixed pitch printed addresses.

7. DISCUSSION

7.1. *Address location*

In the set of machine printed addresses processed, the address location algorithm worked very well, achieving overall correct identification of the address block in 97.6% of the test envelope images and locating part of the address region (sufficient for subsequent classification) in another 2.1% of the test images. The envelope image database used was not deliberately designed to present 'worst case' images, but neither is there any reason to believe it was much less demanding than typical 'live' mail mechanically constrained to conventional envelope sizes.

Results were much less satisfactory for the small set of handwritten and hand printed addresses analysed, not because the algorithm failed to identify the address block, but because in many cases only part of this block was identified. This would be sufficient for subsequent classification into two categories for a culling system, but would be inadequate if the results of the preprocessor were to be fed to two symmetric OCR channels in a presorting system, one for print and one for handwriting. In this latter case, accurate information concerning the extent of the address region would be required for the handwriting channel as well as the print channel.

A possible solution to this problem would be to use a more flexible adaptive system for linking characters and lines together. Yeh *et al.*[5] propose a 'proximity tree' data structure as a method for encoding the relationships between different regions in an envelope image in a hierarchical form. By extracting a histogram of region spacings from the proximity tree and searching for peaks in this histogram corresponding to character, line and region spacings, adaptive thresholds could be specified for grouping characters and lines of the address. Such a system should be capable of improving the performance of the address region extraction algorithm for handwritten and hand printed addresses without compromising performance on printed addresses. This approach would be particularly attractive if combined with some form of pyramidal data structure representation of the image such as an x–y tree or nanotree[26] to minimise computational requirements.

Based upon the results of the present study there seems little need for computationally intensive techniques such as rule-based systems for selecting the final chosen address region if envelopes are constrained to conventional letter sizes. If our data set is representative, only a very small proportion of such mail items have layouts so unusual as to defeat the simple distance measure used here.

7.2. *Address classification*

The various features proposed have the potential to offer reasonable classification performance. However, none of the features as defined in this paper is sufficiently accurate always to distinguish machine printed from hand printed text. Further work is required to decide which subset of features should be used in a final system, and to determine an optimum threshold hypersurface in n-feature space. If this hypersurface can be identified (for example using a large data set, nearest-neighbour methods and the multi-edit and condensing technique,[30] or using a neural network trained on the features described in this paper) performance would be improved compared with our initial heuristic choices.

8. CONCLUSIONS

In this feasibility study, we have reviewed a variety of approaches to the problem of recognising unconstrained addresses on mail pieces, and have then attempted to investigate briefly the overall processing requirements to extract the address region from other data contained in a constrained envelope image. This was achieved by establishing parameters about this region identifying its geometric structure and subdivision into lines and characters, and then classifying the address region according to the requirements of a subsequent OCR system. A key objective was to perform some first level evaluation of these techniques using realistic envelope image data to establish the major problem areas.

Although relatively straightforward, the address location technique chosen appeared to work well and reliably for printed addresses achieving accurate and correct address location in over 97% of cases. Some modifications would however be required to achieve similar performance for handwritten addresses.

Performance of the chosen address classification features was slightly less good, though still promising. Practical performance would in any case depend upon the exact type of system being constructed (a presorter or a culler), the mix of printed and handwritten addresses in the mail handled, and the performance of the OCR system into which the presorter fed its output.

Correct overall classification of 87% or more was achieved both when feature classification thresholds were optimised for presorting performance, and for culling performance. When thresholds were optimised to distinguish between machine readable and non-machine readable classes of address (as previously determined using an AEG OCR system), correct overall classification fell to around 70%. This highlighted the fact that the classification features used to distinguish between print and handwriting were not particularly effective in determining which of a set of machine printed addresses would actually prove to be machine readable by the OCR system.

Simple measures based upon DFT analysis of histograms were found to be able to classify addresses into 'fixed pitch print' and 'other' classes with an accuracy of about 80%.

SUMMARY

This paper reviews the problems involved in locating and recognising addresses on unconstrained mailpieces, and describes a feasibility study to investigate these problems in a restricted domain. Methods of preprocessing binary envelope images to (i) extract the address block from the image in the presence of other data such as postage stamps, logos and postmarks and (ii) presort address blocks into subclasses suitable for recognition by an OCR system with separate channels for machine and handwritten addresses, are proposed and evaluated.

The address block location algorithm smears and reduces the resolution of the envelope image in horizontal and vertical axes, and subsequently locates a single region of connected pixels as the most likely address. Sub-regions of this single region are also extracted: these will normally consist of single words or lines of the address. Based on experiments using 332 envelope images of different printing and handwriting styles extracted from existing OCR sorting equipment installed in a British Post Office sorting office, a correct address block location rate of around 98% was achieved.

Address sorting into handwritten or machine printed channels was achieved using seven measures based on the contour regularity, pixel density and character regularity of the address region. These measures were evaluated on almost 1500 envelope images of various types and a correct sorting rate of around 86% was achieved overall. For compatibility with existing machine printed address OCR sorting equipment, performance in sorting mail samples into channels of currently machine readable (using AEG OCR sorting equipment) and currently not machine readable was also investigated. The results of these experiments show that the measures produced around 70% accuracy in this test.

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