Text Line Aggregation

Christopher Beck[1], Alan Broun[2] Majid Mirmehdi[1], Tony Pipe[2] and Chris Melhuish[2]
[1]*Visual Information Laboratory, University of Bristol, Bristol, U.K.*
[2]*Bristol Robotics Laboratory, University of the West of England, Bristol, U.K.*

Keywords: Text Aggregation, Line Construction, Text Detection.

Abstract: We present a new approach to text line aggregation that can work as both a line formation stage for a myriad of text segmentation methods (over all orientations) and as an extra level of filtering to remove false text candidates. The proposed method is centred on the processing of candidate text components based on local and global measures. We use orientation histograms to build an understanding of paragraphs, and filter noise and construct lines based on the discovery of prominent orientations. Paragraphs are then reduced to seed components and lines are reconstructed around these components. We demonstrate results for text aggregation on the ICDAR 2003 Robust Reading Competition data, and also present results on our own more complex data set.

SCIENCE AND TECHNOLOGY PUBLICATIONS

1 INTRODUCTION

Text localization in natural scenes requires many challenging steps to produce successful results, including the detection of candidate regions (or components), filtering and removal of noisy regions, aggregation into groups, recovery of perspective view, and finally recognition. Figure 1 shows a schematic of this processing pipeline. The focus of our work here is on the text aggregation stage: the coherent sorting, filtering, and grouping of text regions (produced by any method in an earlier text detection stage that returns candidate text regions) into blocks and lines, i.e. understanding how text components are laid out in the scene by determining which candidate regions form individual lines. We work on the assumption that text appears in straight lines and contains three or more characters.

The common trend at the start of the text localization pipeline is the use of a segmentation method to produce connected components, such as (León et al., 2005; Merino and Mirmehdi, 2007; Zini et al., 2009; Epshtein et al., 2010; Pan et al., 2011; Neumann and Matas, 2011b; Merino-Gracia et al., 2011). A series of geometric filters are then applied, for example height, width, aspect ratio, density, roughness and hole count, to remove the majority of non-text components, e.g. as in (Neumann and Matas, 2011b; Merino-Gracia et al., 2011). These filters can have a large effect on the outcome of the system - too strict and text is lost, too slack and system noise is increased. Such outputs at this stage of the pipeline would serve as input into our proposed text aggregation approach.

Text is often contained within structured lines while non-text components often form unstructured and chaotic groupings. The proposed method looks to exploit this structure to filter out false candidate text regions. For the purposes of this work, a *component* is a segmented part of an input image and is stored as a list of pixels, along with its average colour value, and its width and height. A *paragraph* is defined as a collection of components based on their geometric similarities. Under this definition, a paragraph may contain one or more components of text and/or noise. We first look to group components into paragraphs, and then based on local and global measures of the paragraph, we reduce them to Line Seed Components (LSC) where later lines can be formed based on these seed component regions. Finally, components removed in earlier stages are reintroduced back into the line as long as certain compatibility criteria are satisfied.

Next in Section 2, we briefly explore some previous attempts at text line aggregation. The proposed method is presented in Section 3, followed by our experiments and results in Section 4. The conclusions of the work are in Section 5.

Beck C., Broun A., Mirmehdi M., Pipe T. and Melhuish C..
Text Line Aggregation.
DOI: 10.5220/0004817903930401
In *Proceedings of the 3rd International Conference on Pattern Recognition Applications and Methods* (ICPRAM-2014), pages 393-401
ISBN: 978-989-758-018-5
Copyright © 2014 SCITEPRESS (Science and Technology Publications, Lda.)

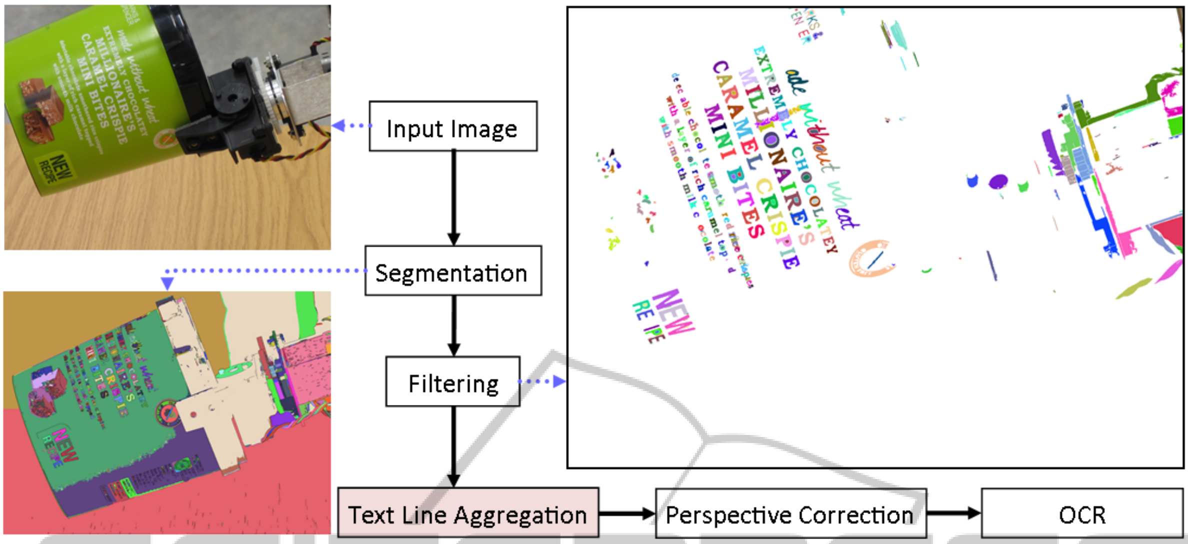


Figure 1: Schematic of a typical text localization method including a text line aggregation step which is the focus of our work.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

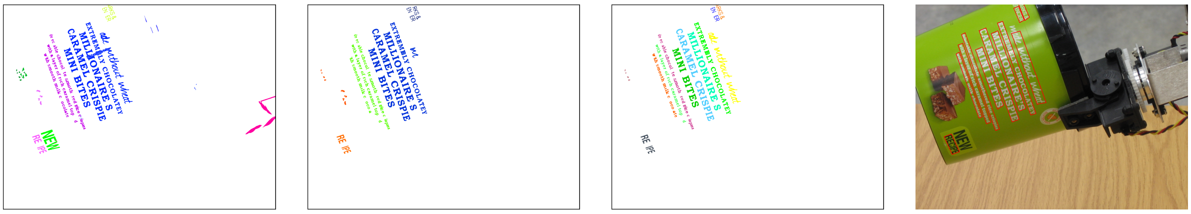
2 RELATED WORK

A substantial amount of work has been carried out in text region localization in everyday scenes (Pilu, 2001; Chen et al., 2004; Chen and Yuille, 2004; León et al., 2005; Liu and Samarabandu, 2005; Liu et al., 2005; Liu and Samarabandu, 2006; Fu et al., 2005; Merino and Mirmehdi, 2007; Retornaz and Marcotegui, 2007; Lintern, 2008; Jung et al., 2009; Zini et al., 2009; Epshtein et al., 2010; Zhang et al., 2010; Pratheeba et al., 2010; Chen et al., 2011; Yi and Tian, 2011; Pan et al., 2011; Neumann and Matas, 2011a; Neumann and Matas, 2011b; Merino-Gracia et al., 2011), with many of them explicitly dealing with the text aggregation stage, such as (Pilu, 2001; Retornaz and Marcotegui, 2007; Epshtein et al., 2010; Neumann and Matas, 2011a; Chen et al., 2011; Pan et al., 2011; Merino-Gracia et al., 2011), although often other terminology was used for it, such as word or line formation. We now focus our review on these specific works, especially as we use several of them for comparative analysis.

An early, but still widely used, method is *pairwise formation*, e.g. as used by Pilu (Pilu, 2001), Epshtein et *al.* (Epshtein et al., 2010), and Chen et *al.* (Chen et al., 2011). The method assumes that text appears in a linear form, and text characters on a line have similar features, such as height, width, and colour. Components are considered to be a pair if they are close in proximity, colour, size, and stroke information (noting that (Pilu, 2001) does not use stroke information). Pairs are merged into strings if they share a component with another pair that appears in the same linear direction (below an orientation threshold), where linear direction is the gradient of the line formed between two paired components. No information is shared globally across the entire string. Based on words being formed by separate unjoined characters, strings with at least three components or more are kept and broken into words based on a measure of spread for the components in the direction of the string. The lack of global information and known orientations in the pairing and merging of component regions means the pairwise formation method is affected by the order in which the components are sampled.

Retornaz and Marcotegui (Retornaz and Marcotegui, 2007) implement a similar method to the pairwise formation philosophy, based on two main steps, merging and alignment. Components are first merged into groups based on three criteria: ratio of bounding box height, and the distances between bounding box's centre in both the vertical and horizontal directions. The groups are encapsulated within a new bounding box that is extended in the horizontal direction for a given distance. If a newly formed box encases another group of components, and which match the three merging criteria, the new group is added, and the process then repeats with a new bounding box. The method is inefficient at removing non-text components, because slanted text lines lead to large bounding boxes that overpower surrounding areas, and introduce a significant level of noise. The method only solves for horizontally laid out text.

Region Graph methods treat components as individual nodes, with links signifying a potential join be-



(a) Paragraph Formation (b) Paragraph Analysis (c) Line Construction (d) Output

Figure 2: Various stages of the proposed text aggregation method (the input text components are shown in Figure 1(top right)).

tween components. Then, filtering the links based on geometric measures produces words and text lines. There are numerous ways to decide whether nodes should be joined by a link. Neumann and Matas (Neumann and Matas, 2011a) form the links by joining each component to the three nearest components on the right, while rejecting links that are in a direction of over 40^o to the normal. Links are removed based on an energy minimization function that uses distance, height ratio, and link angle. The final minimum energy graph will contain separate lines of nodes that represent text lines. Merino et *al.* (Merino-Gracia et al., 2011) also use a region graph, but they implement a Delaunay graph to form links. No minimization is carried out, and instead links are removed based on (a) their angle to the normal (between $\pm 45^o$), (b) link length based on component bounding box, and (c) ratio of component size. Unlike Neumann and Matas (Neumann and Matas, 2011a) who try to minimize the energy, no information is shared across the string as a whole, but only in local pockets. Both (Neumann and Matas, 2011a; Merino-Gracia et al., 2011) are limited to a certain range of orientations, but their work is aimed at text that is horizontal or with a relatively small slope and they focus on the types of images present in databases like ICDAR 2003 (Lucas et al., 2003).

Pang et *al.* (Pan et al., 2011) consider oriented text by employing a minimum spanning tree (MST) approach to produce the region graph. They use the Kruskal algorithm (Sedgewick, 2002) to form the tree, and then like (Neumann and Matas, 2011a) look to minimize the graph energy to form text lines. However, unlike (Neumann and Matas, 2011a) and (Merino-Gracia et al., 2011) who use the angle of orientation in the minimization process, Pang et *al.* (Pan et al., 2011) do not, and in return are not restricted in the range of text orientations their system can handle. Instead, their system uses line regression error, cut score, line height, spatial distance, bounding box distance, and line number to reduce the graph down to lines. The downside to the unrestricted angle of orientation here is the lack of shared orientation information across the group as a whole. This can result in the acceptance of groups that display weak structural formations that are typically present in false positive regions.

Currently, the state-of-the-art methods look to aggregate components into groups based on some form of chaining rule, and then preform some filtering on a local scale to reduce the chains into lines or words. This approach is acceptable when the text is known to be horizontal, or reducing noise is not an issue, but when the orientation is unknown, the methods struggle to produce lines. We hypothesize that a global approach to exploring and removing links from the initial group will solve the unknown orientation problem. This hypothesis is constructed around the principle of forming structured paragraphs from a simple grouping algorithm and then exploiting the structure within the paragraph to build lines.

3 PROPOSED METHOD

Our approach to text aggregation comprises three distinct processes, Paragraph Formation, Paragraph Analysis, and Line Construction (e.g. as in Figure 2(a), 2(b), and 2(c) respectively) and these stages are described in detail below.

The input for the system is an unsorted list of components (e.g. Figure 1(top right)), where each component C_i is represented by a list of pixels, average colour value, and width and height, i.e. $\{L_i, \mu_i, w_i, h_i\}$ respectively. For paragraph formation, we use a similar geometric grouping method as (Pilu, 2001; Retornaz and Marcotegui, 2007; Epshtein et al., 2010; Chen et al., 2011) to produce an initial clustering of components. We do not assume that any group formed during this stage contains text, but only forms a cluster of similar components, be it text, noise or a mixture of the two. Then, we analyse the paragraphs on both a local component level and on a global level across the group as a whole. This analysis attempts to find the dominant orientation in the group and removes uncompromising components. Finally, for line construction, we use the remaining components to form new lines based around known orientations and

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

the idea of a search alley. Components lost in earlier stages are reintroduced if necessary and broken lines are merged.

3.1 Paragraph Formation

Text components within a paragraph often share certain physical similarities, such as proximity, size and colour. We group components based on these attributes and a component is accepted into a paragraph P if it matches sufficiently well with any of its constituent components across all these attributes. The quality of the match is determined by three thresholds (see δ, α, and φ below) which are determined empirically and set to constants for all our experiments. Stray non-text components within a paragraph usually do not fit a uniform pattern set by the majority of its text components and will be removed in later steps.

Proximity - Components must be within close spatial proximity to each other to be considered within the same paragraph P. Given components C_i and C_j, then $(\Delta x, \Delta y)$ is the difference in mean location of both components, such that

$$\Delta x < (w_i * \delta) + (w_j * \delta) \quad \text{and} \quad \Delta y < (h_i * \delta) + (h_j * \delta), \tag{1}$$

where δ is the distance weight. This differs from Ezaki et *al.* 's proximity measure (Ezaki et al., 2004) by using the combined bounding box measurements rather than the maximum, because this reduces the influence of large components on small neighboring components.

Size - In general, text characters in a line will share similar height and width values, and so we compare height/width to aid further filtering during the formation stage. A component C_i is compared to its closest neighboring component C_j from the test paragraph P with

$$\begin{aligned} min(h_i, h_j)/max(h_i, h_j) < \alpha \\ min(w_i, w_j)/max(w_i, w_j) < \alpha \end{aligned} \tag{2}$$

where α is a constant.

Colour - Each component has an average colour value, μ_i, and each paragraph has an average colour value, μ_P, which is updated as new components join. Components must be within a set range for each colour to be allowed in the paragraph. Given φ as the colour difference threshold, then component C_i joins paragraph P if:

$$\varphi > |\mu_i - \mu_P| \tag{3}$$

Components are tested from left to right across the image, and we assume illumination variations can be ignored due to small distances between components in paragraphs. RGB values have been used in this work.

3.2 Paragraph Analysis

Each component is measured to produce a local understanding that leads to a basic global knowledge of the whole paragraph. The dual analysis of local and global characteristics allows for an aggressive filter that rejects noise (non-text) components, but maintains strong text like components (LSCs) that later will form the foundation for line construction.

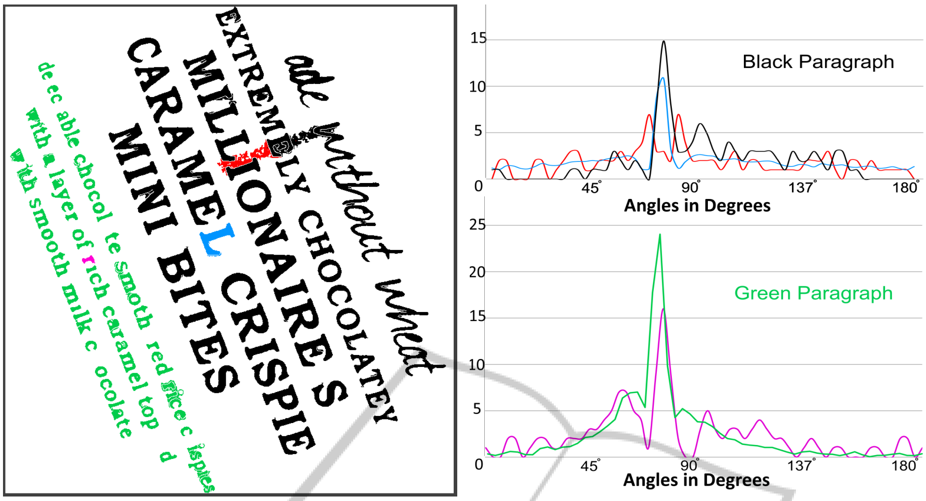
Local Measures - Two measures are produced from the local analysis. First, a mode orientation value ν is computed for each component by histogramming the angle of the vectors from its centroid to the centroid of every other component in P. These orientation angles are normalized to be between 0°-180° to reduce the effects of components that lie on a line either side of the current component. We use a histogram with bin width $\xi = 6°$. Figure 3(a) shows two paragraphs in black and green with three highlighted components ('L', a noise region, and 'r'). Figure 3(b) shows the corresponding histograms for the three highlighted components and for each whole paragraph (averaged across its respective components). The overall orientation of the paragraphs are clearly visible from the dominant peaks.

Next, the orientation variance is first found for each component by normalizing the orientations of all other components onto a unit circle. The normalization ensures that components that lie 90° apart when measured from the centroid of the current component cancel across the unit circle, while components that appear 180° apart compared to the current component lie in the same location on the unit circle. The confidence value κ is then computed, as a second measure, as the displacement of the average locations from the centre of the circle, and its value will be between 0 and 1.

Global Measures - The paragraph orientation P_ν is the highest scoring bin obtained by histogramming all the local mode values ν weighted by their corresponding confidence value κ into a similar histogram as that used above. The paragraph confidence value P_κ is the average of all the confidence values that contributed to the winning histogram bin, and its value will be between 0-1.

Once the local and global measures are available, paragraph confidence values P_κ below a generous threshold are removed altogether as noise paragraphs. Then, each component in the remaining paragraphs must have a local orientation within a bin width ξ of its own paragraph's orientation P_ν, otherwise it is removed from that paragraph, but remains a member of it for later line construction purposes.

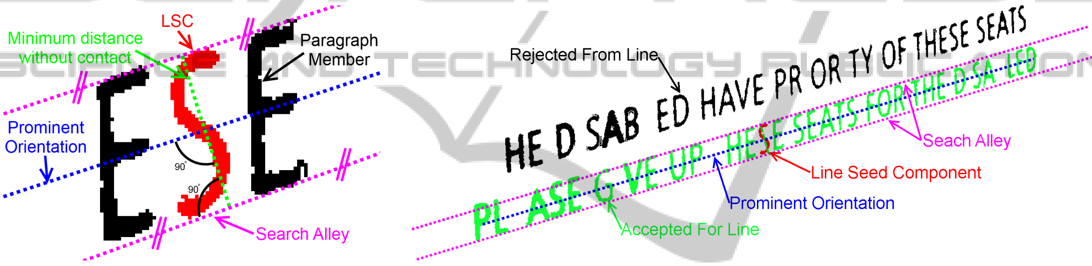
This filtering is a harsh step due to the fluctuation



(a) Two example paragraphs (b) Their orientation histograms

Figure 3: Example orientation histograms shown in corresponding colour: black for black paragraph, blue for component region 'L', red for noise region, green for green paragraph, and pink for component region 'r'.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS



(a) Search Alley Construction (b) Construction of Lines

Figure 4: The construction of a search alley and forming a line around a seed component.

in character heights and mean locations, and may remove a large portion of valid characters within a paragraph. The remaining characters become Line Seed Components or LSCs as defined earlier. There is no limit on the number of LSCs produced - a paragraph or line may be composed of all LSCs, but as will be seen only one is required to form a line and to populate it with components. This step has a high rejection rate while producing LSCs.

3.3 Line Construction

Line Construction consists of three key stages. Seed components are used to perform basic line formation with other members of the paragraph, lines are merged with other lines from within and different groups, and some originally removed components that satisfy certain criteria are reintroduced along the line.

Initial Formation - A seed component is randomly chosen from the group of LSCs. Figure 4(a) shows how a search alley is constructed from two lines parallel to the prominent orientation that have a minimum perpendicular distance from each other but do not touch the seed component. Figure 4(b) shows the construction of lines around a LSC. The closest component (including those from paragraph filtering in the last step) whose mean location falls within the alley is added to the line, and becomes the new seed. The process is repeated until no new component is added to the line. A new seed is then chosen from the remaining LSCs in the paragraph and the whole formation process is repeated for a new line until all LSCs have been tested. A line must contain three or more components after formation. A straight line is fitted using least squares.

Line Merging - Two lines a and b are merged into one if they share a similar gradient ∇, e.g. smaller than ξ (the bin width):

$$|\nabla^a - \nabla^b| < \xi \tag{4}$$

They must also have ends in close spatial proximity

$$\sqrt{|x^a - x^b|^2 + |y^a - y^b|^2} < \Lambda \tag{5}$$

where Λ equals four times the value of the average width of a component in paragraph P along the line.

Figure 5: Examples from the (top row) ICDAR (Lucas et al., 2003) and (bottom row) Text-IVu 2014 Dataset.

Table 1: Comparative Precision/Recall results for the ICDAR data set.

ICDAR 2003 Robust Reading Competition Data									
	MSER		SWT		CCOM		Manual		t
Method	*Prec*	*Rec*	*Prec*	*Rec*	*Prec*	*Rec*	*Prec*	*Rec*	(ms)
Pairwise (Pilu, 2001)	0.68	0.57	0.71	0.66	**0.75**	0.64	1.00	0.87	348
Merge & Align(Retornaz and Marcotegui, 2007)	0.51	0.46	0.51	0.46	0.47	0.49	1.00	0.81	509
Graph Energy (Neumann and Matas, 2011a)	0.61	0.58	0.67	0.55	0.59	0.60	1.00	0.88	714
MST (Pan et al., 2011)	**0.72**	**0.68**	**0.78**	**0.70**	0.69	0.64	1.00	**0.92**	948
Delaunay (Merino-Gracia et al., 2011)	0.55	0.63	0.64	0.60	0.58	**0.67**	1.00	0.82	**325**
Proposed method	0.66	0.66	0.73	0.68	0.65	0.64	1.00	0.89	957

Our evaluations showed 95% of split lines separated by one or more missing characters are less than four average widths apart. This split is often caused by wide horizontal characters like ‘m’ or ‘w’ that lay between thin vertical characters like ‘i’ or ‘p’.

Component Reintroduction - Components rejected earlier during the initial grouping or paragraph analysis stages are revisited and if any appear within a line’s search alley and shares similar geometric values (i.e. (2)) and colour values (i.e. (3)), and lies within Λ, are added to the line.

4 EXPERIMENTS

Our method is applied to two different data sets, the widely used ICDAR 2003 Robust Reading Competition Dataset (Lucas et al., 2003) and our own Text-IVu 2014 Dataset [1]. We use these two different data sets because the ICDAR 2003 data set mostly contains single word lines that are of a very limited range of orientations and perspectives, while the Text-IVu 2014 Dataset covers a wide range of orientations, perspectives and line lengths. The former is thus more suitable for methods that are tuned to a horizontal search process, whereas the latter offers greater challenges.

[1] www.brl.ac.uk/researchthemes/robotvision

The images in the ICDAR 2003 dataset (Lucas et al., 2003) and the Text-IVu 2014 Dataset were processed to generate candidate text components as input into the proposed method for text aggregation using four separate approaches: manually annotated components, the maximally stable external regions method (MSER) (Nistér and Stewénius, 2008), the stroke width transform (SWT) (Epshtein et al., 2010), and the classic connected components (CCOM). The manually annotated images contain only true text components, while the others include both text and false positive non-text components.

We show precision and recall results on the number of components recovered, and the average computing time per image for each method.

ICDAR 2003 Robust Reading Competition Data - The ICDAR 2003 data set (Lucas et al., 2003) is a publicly available set of 251 images in a range of sizes for the comparison of text localization methods (e.g. see top row of Figure 5). It contains a variety of images where text is the primary focus and dominates much of the image with usually a single short text string or region. Of the 251 images, only 10 can be considered to contain text that neither lie close to the horizontal plane nor are fronto-parallel to the camera, i.e. 96% of the images contain horizontal text.

We compare our proposed method for text line

Table 2: Comparative Precision/Recall results for the Text-IVu 2014 Dataset.

Text-IVu 2014 Dataset									
	MSER		SWT		CCOM		Manual		*t*
Method	*Prec*	*Rec*	*Prec*	*Rec*	*Prec*	*Rec*	*Prec*	*Rec*	(ms)
Pairwise (Pilu, 2001)	0.54	0.56	0.59	0.61	0.57	0.54	1.00	0.46	726
Merge & Align (Retornaz and Marcotegui, 2007)	0.48	0.44	0.47	0.38	0.43	0.41	1.00	0.48	781
Graph Energy (Neumann and Matas, 2011a)	0.35	0.37	0.43	0.41	0.38	0.36	1.00	0.40	1304
MST (Pan et al., 2011)	0.57	0.55	0.54	0.48	0.49	0.51	1.00	0.78	1550
Delaunay (Merino-Gracia et al., 2011)	0.41	0.38	0.42	0.40	0.38	0.45	1.00	0.43	**517**
Proposed method	**0.60**	**0.64**	**0.61**	**0.63**	**0.62**	**0.57**	1.00	**0.80**	1431

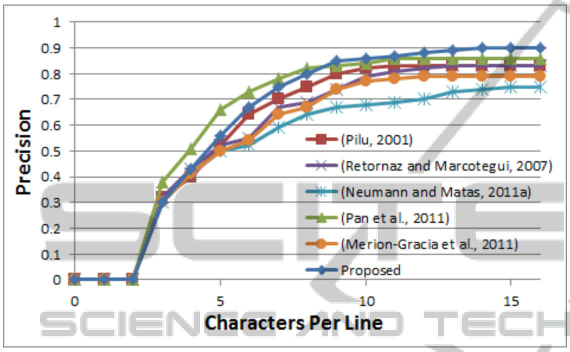


Figure 6: Precision rates for location compared against line length.

Figure 7: Failed word ("Jungle") due to large variation in angles. Note "COM" is found in this case.

aggregation against the text aggregation parts of five different methods. These are our implementations of Pilu (Pilu, 2001) (Pairwise), Retornaz and Beatriz (Retornaz and Marcotegui, 2007) (Merge & Align), Neumann and Matas (Neumann and Matas, 2011a) (Graph energy), Merino et *al.* (Merino-Gracia et al., 2011) (Delaunay), and Pang et *al.* (Pan et al., 2011) (MST). Table 1 shows the results of all the different aggregation methods on the ICDAR 2003 data set for different segmentation methods.

As seen in Table 1, our method preforms well against the other techniques, but it can be said to fall short on the ICDAR data set due to the data's comparatively small average line length of 8 components per line. Figure 6 shows how all the methods experimented with perform similarly on short line lengths and see an increase in performance as the length increases. Our method shows it is weaker on shorter lengths, but dominates on the longer lengths. Shorter line lengths do not produce enough data points in the orientation histogram and so fail to establish a dominant orientation. Figure 7 shows an example when our method will fail, i.e. the word "Jungle" is not found as it produces a large range in angles and no conclusive histogram bin value, whereas extreme outliers are less of a problem in longer lines. The reliance on longer lines allows the system to better handle noise and orientations. Our approach is thus less suited to shorter line lengths.

Text-IVu 2014 Dataset - The nature of the data in this data set is quite different to that of the ICDAR dataset (Lucas et al., 2003) in that it contains images with substantially more text in larger groups and at more varied orientations and perspectives (e.g. see bottom row of Figure 5). For example, the scenes in this data set are more likely to be encountered by robots or blind users when holding objects with text written on them. The data comprises of 50 colour training images and 403 colour test images, all at various resolutions taken by several digital cameras in both indoor and outdoor environments spanning a variety of text sizes and orientations, and includes images affected by poor lighting conditions and specular reflection. Approximately 20% of the Text-IVu 2014 Dataset contains text that lies close to the horizontal plane and 35% of scenes contain multiple text orientations.

Comparing Table 2 with the previous table, it becomes clear that all methods see a drop in performance and an increase in computational expense due to the more challenging nature of the Text-IVu 2014 Dataset. However, the proposed method is the best performing method given any of the different segmentation methods. The average line length in the Text-IVu2014 Dataset is 27 components per line and this means our system is better able to establish a dominant orientation and so deals with complex scenes

Table 3: Line accuracy for the Text-IVu 2014 Dataset.

Parameter Tuning for Proposed Method						
Parameters				Evaluators		
δ	α	φ	ξ	*Prec*	*Rec*	t (*ms*)
1.6	1.5	50	6°	0.61	0.62	517
1.4	1.5	50	6°	0.62	0.58	504
1.8	1.5	50	6°	0.58	0.64	563
1.6	1.3	50	6°	0.63	0.59	511
1.6	1.7	50	6°	0.60	0.64	548
1.6	1.5	25	6°	0.64	0.52	480
1.6	1.5	75	6°	0.37	0.73	623
1.6	1.5	50	3°	0.63	0.51	498
1.6	1.5	50	9°	0.37	0.73	623

better than the other techniques. Over-compensating for short lines will increase the recall of the system but at a cost of the precision.

Parameter Tuning - For fairness of comparison and despite the varied nature of the two data sets, the threshold values in all methods were kept the same for all experiments. The optimal value for each method was determined empirically from the training sets provided with the ICDAR 2003 data set (Lucas et al., 2003) and the Text-IVu 2014 Dataset. The optimal values for the proposed method were δ=1.6, α=1.5, and φ=50. Table 3 shows the effect of changing one parameter above or below the optimal value. Figure 8 is a normalised ROC graph that shows the classification of components after the line formation for these parameters. It should be noted that these paragraph formation thresholds were set to be restrictive in their grouping. Although this sees the rejection of true components, it greatly reduces noise in later stages and lost components can be retrieved after the construction of lines.

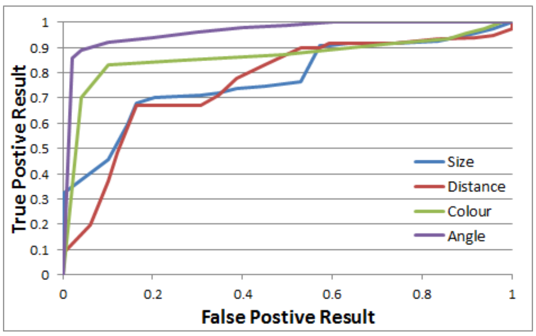


Figure 8: ROC for parameter values from Text-IVu2014 training set.

Table 4 and Table 5 show precision, recall, and accuracy values for text line construction for the ICDAR data set (Lucas et al., 2003) and Text-IVu 2014 Dataset respectively. Accuracy shows that for a given line what proportion of its characters have been recovered.

Table 4: Line accuracy for the ICDAR data set.

ICDAR 2003 Robust Reading Competition Data			
	Line Accuracy		
Method	*Prec*	*Rec*	*Acc*
Pairwise (Pilu, 2001)	0.73	0.74	0.71
Merge & Align (Retornaz and Marcotegui, 2007)	**0.75**	0.73	**0.90**
Graph Energy (Neumann and Matas, 2011a)	0.63	0.66	0.70
MST (Pan et al., 2011)	0.65	**0.77**	0.71
Delaunay (Merino-Gracia et al., 2011)	0.63	0.68	0.69
Proposed method	0.71	0.74	0.89

Table 5: Line accuracy for the Text-IVu 2014 Dataset.

Text-IVu 2014 Dataset			
	Line Accuracy		
Method	*Prec*	*Rec*	*Acc*
Pairwise (Pilu, 2001)	0.67	0.73	0.65
Merge & Align (Retornaz and Marcotegui, 2007)	0.61	0.58	0.80
Graph Energy (Neumann and Matas, 2011a)	0.54	0.61	0.55
MST (Pan et al., 2011)	0.61	0.74	0.58
Delaunay (Merino-Gracia et al., 2011)	0.56	0.64	0.67
Proposed method	**0.74**	**0.78**	**0.86**

For the ICDAR data in Table 4, Retornaz and Beatriz (Retornaz and Marcotegui, 2007) obtain only a marginally better accuracy of 0.90 than the proposed method at 0.89, while in terms of precision and recall, we stand we compare well against the other methods. For the Text-IVu 2014 Dataset in Table 5, our method exceeds all others by a good margin due to its better handling of unknown orientations and the recovery of lost characters that lie on the outer edges of groups.

5 CONCLUSIONS

Text line aggregation is a challenging problem due to the varying styles of text and layouts within an unconstrained natural scene. We have presented a method that is capable of dealing with complex scenes containing a large variety of text at various orientations. It is suitable as a plug-in module to a range of text segmentation systems. We have introduced the Text-IVu 2014 dataset which is more challenging, complex and truer to real life situations compared to the ICDAR 2003 Robust Reading Competition Data. The system is still constrained by the assumptions of straight lines, and the number of text components per line.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

These are issues we hope to address in future work.

REFERENCES

Chen, H., Tsai, S., Schroth, G., Chen, D., Grzeszczuk, R., and Girod, B. (2011). Robust text detection in natural images with edge-enhanced maximally stable extremal regions. In *ICIP*, pages 2609 – 2612.

Chen, X., Yang, J., Zhang, J., and Waibel, A. (2004). Automatic detection and recognition of signs from natural scenes. In *ICIP*.

Chen, X. and Yuille, A. (2004). Detecting and reading text in natural scenes. In *CVPR*, volume 2, pages II – 366.

Epshtein, B., Ofek, E., and Wexler, Y. (2010). Detecting text in natural scenes with stroke width transform. In *CVPR*, pages 2963–2970.

Ezaki, N., Bulacu, M., and Schomaker, L. (2004). Text detection from natural scene images: towards a system for visually impaired persons. In *ICPR*, volume 2, pages 683 – 686.

Fu, L., Wang, W., and Zhan, Y. (2005). A robust text segmentation approach in complex background based on multiple constraints. In *AMIP-PMC*, pages 594 – 605.

Jung, C., Liu, Q., and Kim, J. (2009). A stroke filter and its application to text localization. In *PRL*, volume 30, pages 114 – 122.

León, M., Mallo, S., and Gasull, A. (2005). A tree structured-based caption text detection approach. In *ICVIPP*, page 220.

Lintern, J. (2008). Recognizing text in Google Street View images. *Statistics*, 6.

Liu, X. and Samarabandu, J. (2005). An edge-based text region extraction algorithm for indoor mobile robot navigation. In *ICMA*, volume 2, pages 701 – 706.

Liu, X. and Samarabandu, J. (2006). Multiscale edge-based text extraction from complex images. In *ICME*, pages 1721 – 1724.

Liu, Y., Goto, S., and Ikenaga, T. (2005). A robust algorithm for text detection in color images. In *ICDAR*, pages 399 – 403.

Lucas, S. M., Panaretos, A., Sosa, L., Tang, A., Wong, S., and Young, R. (2003). ICDAR 2003 robust reading competitions. In *ICDAR*.

Merino, C. and Mirmehdi, M. (2007). A framework towards realtime detection and tracking of text. In *CBDAR*, pages 10 – 17.

Merino-Gracia, C., Lenc, K., and Mirmehdi, M. (2011). A head-mounted device for recognizing text in natural scenes. In *CBDAR*, pages 29 – 41.

Neumann, L. and Matas, J. (2011a). Estimating hidden parameters for text localization and recognition. In *Computer Vision Winter Workshop*.

Neumann, L. and Matas, J. (2011b). A method for text localization and recognition in real-world images. In *ACCV*, pages 770 – 783.

Nistér, D. and Stewénius, H. (2008). Linear time maximally stable extremal regions. In *ECCV*, pages 183 – 196.

Pan, Y., Hou, X., and Liu, C. (2011). A hybrid approach to detect and localize texts in natural scene images. *Image Processing, IEEE Transactions on*, 20(3):800 – 813.

Pilu, M. (2001). Extraction of illusory linear clues in perspectively skewed documents. In *CVPR*, volume 1, pages I – 363.

Pratheeba, T., Kavitha, V., and Rajeswari, S. (2010). Morphology based text detection and extraction from complex video scene. *IJET*, 2(3):200 – 206.

Retornaz, T. and Marcotegui, B. (2007). Scene text localization based on the ultimate opening. In *ISMM*, volume 1, pages 177 – 188.

Sedgewick, R. (2002). Algorithms in C, Part 5: Graph Algorithms.

Yi, C. and Tian, Y. (2011). Text string detection from natural scenes by structure-based partition and grouping. *Image Processing, IEEE Transactions on*, 20(9):2594 – 2605.

Zhang, Z., Lu, T., Su, F., and Yang, R. (2010). A new text detection algorithm for content-oriented line drawing image retrieval. In *Advances in Multimedia Information Processing-PCM*, pages 338 – 347.

Zini, L., Destrero, A., and Odone, F. (2009). A classification architecture based on connected components for text detection in unconstrained environments. In *AVSS*, pages 176 – 181.