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웨이블릿패킷분석을 이용한 문서영상에서의 텍스트/비텍스트 검출 방법

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Odoyo O. Wilfred

CONTENTS

ABSTRACT

A Text / Non-text Detection method in Document Image using Wavelet Packet Analysis

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문서의 자동화된 처리와 해석은 통신과 IT 분야의 진보와 더불어 그 수요가 증가되고 있다. 디지털화된 형태로 문서를 저장하기 위한 노력이 계속되고 있으나 압축기술의 발달에도 불구하고 거대한 저장공간이 요구되고 있는 실정이다. 문서들을 텍스트와 그래픽 영역으로 분리하고 텍스트 부분은 아스키 형태로 그래픽 부분은 비트맵 형태로 저장하여 데이터베이스로 구축한다면 문서에서 텍스트 부분의 효율적인 탐색과 저장이 용이하게 될 것이다. 문서영상 내의 그래픽 영역은 텍스트 영역과 구분되는 텍스쳐 속성을 갖는다고 가정하며, 세그멘테이션 방법은 문서영상을 웨이블릿패킷으로 분해하는 웨이블릿 분석과 통계학적 패턴인식 개념들을 사용한다. 다양한 채널들은 주파수 평면에서 멀티스케일과 다중방향의 영상을 찾아내고, 채널들의 결합은 에지를 변형시켜 불연속선 검출이 가능하게 한다. 그리고 멀티스케일상의 특징벡터를 구한 후, K-means 클러스터링 알고리즘으로 텍스트/비텍스트 영역을 세그멘테이션 한다. 본 논문은 폰트크기, 스캐닝해상도, 레이아웃 형태 등 어떤 사전정보도 없이 실험하였으며, 실험결과는 텍스트/비텍스 영역을 잘 찾아내고 있음을 보여준다.

List of Figures

List of Tables

I. Introduction

Document image segmentation is an act of partitioning a document image into separated regions. These regions should ideally correspond to the image entities such as text blocks and non-text blocks. This is the task that most researchers in this field are faced with. Many techniques have been proposed to segment the document image into text and non-text regions in the literature [1]. Wavelets techniques have become very handy in this area of document image analysis. They are particularly good at describing a scene in terms of the scale of textures in it.

Texture is an important property of reflective surface which human visual perception system uses to segment and classify different image objects in a digital image. Our method of document image segmentation also is a type of wavelet based on multiresolution analysis which are very effective in the study of complex signals and images. In this paper, we propose a new wavelet based approach for document image segmentation called wavelet packet analysis, which, according to our experimental result, show an upper hand over other traditional single resolution methods of document image segmentation.

The first step, as in all other texture-based document image segmentation is the texture extraction. Wavelet packet analysis provides a wider spectrum for richer feature extraction from the recursive decomposition of both the approximation and the detail coefficients derived from the original signal. This splitting of both the approximation and detail coefficients offer more complex and flexible analysis with many bases (subbands) from which we can look for the best representation.

Section II of this work dwells on the related work and research that has been going on in this area based on almost similar methods. The next part which is section III gives a brief introduction to what wavelets are and the types of wavelets. It is in this section that we present our algorithm for wavelet packet analysis. $k-means$ clustering method is applied during segmentation. Other components discussed here include local energy estimation, computing standard deviation, nonlinearity, smoothing and gaussian blurring are involved in this step. Potential of the proposed algorithm is shown in the experiments and results, part section IV. Original images are shown, their decompositions and final segmentation images. We conclude our paper in section V with possible future work.

II. Relatedw ork

Document Image Segmentation is a crucial step in the conversion process for paper document images into electronic documents. With the advances in communication and information technology, there is an inevitable need of automated processing and reading of such documents. Modern techniques have been successfully applied to compress large documents to be stored in databases, but still, every time we run out of space due to the bulkiness of the data to be stored.

By now, a lot of papers have been published and practical research and development have been partially achieved on the field of document image segmentation [2]. This has been done through several techniques with the most explored methods being bottom-up, top-down, and a hybrid of the two, known as split-and-merge algorithms. These are grouped as hierarchical methods because the geometric relationship among blocks formed in the page document is considered.

Top-down approach, which is kind of knowledge based, proceeds with an expectation of the nature of document. It avoids bad decisions by considering the entire image in question, in its very first step of iteration. Here the page is split into blocks which are subsequently identified and subdivided further until all regions are deemed homogeneous. For example, one may decide to first locate major columns in the page splitting them further into paragraphs, text lines, words and eventually characters. Some algorithms which use the top-down approach include recursive projection profile cuts [3, 4], run length smoothing and constrained run length [5]. The constrained run length algorithm works this way; starts from the binary image and replaces every string of contiguous 0′s representing white pixels, less than a threshold predetermined, by a string of 1′s representing black pixels, of the same length. The process binary smearing is performed in both horizontal and vertical directions and the logical "AND" is used in the final bit-map to obtain the two outputs.

Although these algorithms make globally optimal decisions, on the other hand they are limited to splitting the entire page even when that does not give us the best results. Also it is difficult to avoid repeating past work which in turn reduces the performance. For more examples of the top-down approach [6] and Fujisawa et al. [7].

Another well known image processing technique is the bottom-up. This approach is data-driven, that is; it progressively refines the data by layered grouping operations. Two practical bottom-up methods are neighborhood line density(NLD), which indicates the complexity of characters and graphics, and connected components analysis indicating the component properties of the document blocks. Such bottom-up tools like connected components [8], begin analysis from pixel level and merge regions together into larger components. It is "region growing" because it starts from isolated areas of the image, enlarges them and repeatedly concatenating all the neighboring pixels till a region border is formed. Basically, the analysis begins from characters, then words, text lines, paragraphs, etc. Though the method is time consuming and the optimal outcome depends on the decision on a small amount of initial data which might lead to bad segmentation, some good examples have been seen [9, 10].

Each of the two methods mentioned above have their short falls prompting the need for more efficient and less time consuming algorithms. Split-and-merge algorithm is a combination of the two trying to offset the trade off between the two but it is also slow. It combines the best features of both the top-down and bottom-up algorithms. Split-and-merge algorithms act like top-down algorithms in that they recursively subdivide the image. Once the regions are homogeneous, they are classified as one of the possible image types. The merging step used in the bottom-up is applied here to combine the neighboring regions of the same type. As have been mentioned, they provide the best on both worlds but are usually slow for any real time application [11].

The methods discussed, to some extent, can be said to depend on some a priori information. They could assume a priori knowledge about the generic document layout structure, for example, rectangularity of major blocks in the image, horizontal and vertical spacing and independence of text, graphic and image blocks, and assumptions about attributes such as font size and text line orientation. This knowledge results in a more efficient page decomposition system but on the other hand limits the range of applicability of the algorithms. To cite a few examples, methods based on projection profiles fails if the page layout is complex, the document page is skewed (ragged), and if the text strings have different orientations. Methods have been developed for measuring and correcting skew angle even though these methods have limited range and add to the complexity of the system.

A number of other approaches regard a homogeneous region (e.g., text, image, and drawing) in a document image as a textured region. Page segmentation is then implemented by finding textured regions in gray-scale images. Representative approaches are methods which uses Gabor filtering and mask convolution, [12, 13, 14], fractal signature [15], and wavelet multi-scale analysis [16] which has the advantage of segmenting nonblock-nested pages. More flexible methods of page segmentation have been explored recently. This is based on the analysis of background white space [17, 18]. This scheme is based on tracking major white spaces between printed components to identify boundaries. In addition to the above mentioned approaches which share some common features, two other methods [19], which uses white tiles to extract contours of regions and features for classification, and [20], a global-to local strategy used in geometric layout analysis which can accommodate different languages in the document.

Algorithms developed based on a priori knowledge as we have seen are limited in their applicabilities. It is therefore, desirable to have segmentation methods that do not assume a priori knowledge about the content and attributes of the text, or about the boundaries of major blocks as with the top-down case. Methods with wide range of application which are robust to skew, noise and other degradation should be developed. A lot of difficulties are on researchers way to achieving this vital goal in document image segmentation. These obstacles can be noted as:

- Noise and degradation caused by various factors such as copying, scanning, transmission or aging.
- Page skew and text regions with different orientations.
- Text regions that touch or overlap unto image and graphics components.
- Varying text and background gray levels combined together as in inverted texts, etc.
- Complex and irregular layout structures that are common especially in non - technical documents.
- Curved lines or multi-column pages where text lines in different columns are not of the same size and / or not aligned.
- Language difference, font sizes and other textual attributes add to the problem.

III. Document Image Segmentation Method

A. Wavelets

a). What is Wavelet?

Historically, wavelet analysis is a new method, though its mathematical underpinnings date back to the work of Joseph Fourier in the nineteenth century (Wavelet Toolbox). The foundations of his theories of frequency proved to be enormously important and influential. Research work on this area has turned from frequency-based analysis to scale-based analysis since frequency alone is less sensitive to noise. Wavelet is fundamentally defined as a waveform of effectively limited duration that has an average value of zero. This analysis has quite a number of advantages over traditional sine waves, the basis of Fourier analysis. Sinusoids tend not to have limited duration and extend from negative to positive infinity. Furthermore, sinusoids are smooth and predictable while wavelets are irregular and asymmetric. Intuitively, signals with sharp changes are better handled with an irregular wavelet than a smooth sinusoid. A major advantage that is afforded by wavelets is the ability to perform local analysis, ie. to analyze a localized area of a larger signal.

Wavelet decomposition which consist mainly of de-noising and compression has two aspects; scale aspects and time aspects. Note that scaling a wavelet simply means stretching (or compressing) it. Both of these aspects have specific goals that they accomplish. Scale aspect, which uses the wavelet technique of regularity study is applied in various fields of biology for cell membrane recognition to distinguish the normal from the pathological membranes, metallurgy for the characterization of rough surfaces, finance and in internet traffic description. On the other hand, time aspects has its goal directed towards rupture and edges detection, the study of short-time phenomena as transient processes In general, wavelet decomposition has many applications concerning signal or image clearance and simplification which are part of de-noising and compression.

b). Types of wavelets.

There are a number of different types of wavelet families whose qualities vary according to several criteria. Most of them have proven to be useful and are included in the wavelet toolbox.

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Table 3-1; Wavelet families included in the wavelet toolbox

Wavelet Family Short Name	**Wavelet Family Name**
'h a a r'	Haar wavelet
'd b'	Daubechies wavelets
's y m'	Symlets
'c o i f'	Coiflets
'b i o r'	Biorthogonal wavelets
'r b i o'	Reverse biorthogonal wavelets
'm e y r'	Meyer wavelet
'd m e y'	Discrete approximation of meyer wavelet
'g a u s'	Gaussian wavelets
'm e x h'	Mexican hat wavelet
'm o r l'	Morlet wavelet
'c g a u'	Complex Gaussian wavelets
's h a n'	Shannon wavelets
‘f b s p'	Frequency B−spline wavelets
'c m o r'	Complex Morlet wavelets

These wavelets can be grouped according to their properties.

Crude wavelets

Infinitely regular wavelets

Orthogonal and compactly supported wavelets

Biorthogonal and compactly supported wavelet pairs

Complex wavelet

The first category includes gaussian wavelets, morlet and mexican hat. They all have minimal properties like wavelet function $\varnothing$ does not exist, analysis is not orthogonal, scale function ψ not compactly supported and reconstruction property not insured. The brighter side of the wavelets in this category include continuous decomposition with the main properties being symmetry and the ψ function having explicit expression. The main disadvantage is that fast algorithm and reconstruction not available.

Infinitely regular wavelets include meyer and discrete meyer wavelets. In meyer, scaling function $\varnothing$ exists and orthogonal analysis is possible. Both scaling and wavelet functions are indefinitely derivable but not compactly supported. Continuous and discrete transform analysis are possible with the latter reconstructed without FIR filters. Symmetry reconstruction and infinite regularity are the main characteristics here but disadvantaged on the algorithm which is not fast. Discrete meyer's general properties include FIR approximation of the meyer wavelet with both continuous and discrete transform analysis possible.

Next is orthogonal and compactly supported wavelets which include the widely used daubechies, symlets and coiflets wavelets. The scaling function exists and the analysis is orthogonal with both scaling and wavelet functions compactly supported. The wavelet function has a given number of vanishing moments. Both continuous transform and discrete transform analysis using FTW available. Away from the poor regularity they face, these wavelets support vanishing moments and FIR filters.

Biorthogonal and compactly supported wavelet pairs include B-splines biorthogonal wavelets with the properties of scaling function and biorthogonal analysis. Construction and reconstruction of both scaling and wavelet functions are compactly supported and have vanishing moments with reconstructions having known regularity. Possible analysis are similar with the orthogonal and compactly supported wavelets.

Main properties are symmetry with FIR filters, desirable properties for decomposition and reconstruction are split and nice allocation available. Biorthogonality is sometimes lost in these wavelets.

The last but not least in the category list is the complex wavelet. There are quite a number of wavelets here including complex gaussian, complex morlet, complex shannon and complex frequency B-spline. Minimal properties like no scaling function, analysis is not orthogonal, wavelet function is not compactly supported, and reconstruction property is not insured. Complex continuous decomposition analysis is possible. Perfect properties are the symmetry on the side of decomposition and wavelet function has explicit expression.

B. Haar Wavelets[1]

Haar wavelets which is an equivalent of Daubechies db1 is the first and the simplest. To grasp the basis of all the wavelet families mentioned above, we will discuss Haar wavelet decomposition here. For example, let us start with a simple one-dimensional image with a resolution of four pixels, having values

$$[\ 9 \quad 7 \quad 3 \quad 5\ ]$$

We can present this image in the Haar basis by computing a wave transform. To do this we first average the pixels together, pairwise, to get the new lower resolution image with the pixel values

[8 4]

8 is the average of the first two pixels 9 and 7 while 4 is the average of 3 and 5. It is very clear that some information has been lost in this averaging process. The original four pixels can be recovered from the two average values in the form of detail coefficients. The detail coefficients captures and stores missing information. The number, 1, is the first detail coefficient since the average we computed is 1 less than 9 and 1 more than 7, and can help us recover the first two pixels of our original four-pixel image. The second detail coefficient is -1 since 4 + (-1) equals 3 and 4 - (-1) is 5. This process is repeated for a lower resolution version and a pair of detail coefficients. A full decomposition of our one-dimensional image example is given below.

Table 3-2 shows one-dimensional decomposition

Resolution	Averages	Detail coefficients
4	[9 7 3 5]	
2	[8 4]	[1 −1]
1	[6]	[2]

The wavelet transform, also known as wavelet decomposition, is defined as the single coefficient representing the overall average of the original image, followed by the detail coefficients in order of increasing resolution. Therefore, in Haar basis, the wavelet transform our original one-dimensional image is given by

[6 2 1 -1]

This method of averaging and differencing coefficients to compute the wavelet transform is know as a filter bank. This process shows no loss or gain of information in the image, as the original image had four coefficients which is the same number of coefficients with the transform. Given the transform, we can reconstruct the image to any resolution by recursively adding and subtracting the detail coefficients from the lower resolution versions. Image's wavelet transform help reduce the image size and the detail coefficients are stored in a very small magnitude.

a). One-dimension Haar wavelet basis function

Above, one-dimensional images have been treated as sequences of coefficients. We also can think of images as piecewise-constant functions on the half-open interval
[0, 1) by using the concept of linear space. A one-pixel image is just a function that is constant over the entire interval [0, 1) while a two-pixel image has two constant pieces over the intervals [0, 1/2) and [1/2, 1). We call the space containing the functions 1 and 2 V^0 and V^1 respectively. V^j will therefore include all piecewise-constant functions defined on the interval [0, 1), with constant pieces over each of 2^j equal subintervals. Thus, the spaces V^j are nested;

$$V^0 \subset V^1 \subset V^2 \subset \ldots$$

The basis functions for the spaces V^j are called scaling functions, and are usually denoted by the symbol $\varnothing$. A simple basis for V^j is given by the set of scaled and translated 'box' functions:

$$\varnothing_i^j(x) := \varnothing(2^j x - i), \quad i = 0, \ldots, 2^j - 1,$$

where

$$\varnothing(x) := \begin{cases} 1 & \text{for } 0 \le x < 1 \\ 0 & otherwise \end{cases}$$

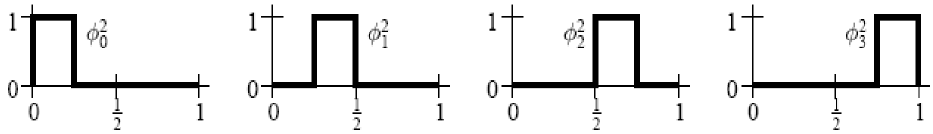


Figure 3-1; Four box functions showing a basis for V^2.

The standard inner product defined on the vector space V^j is

$$\langle f|g \rangle := \int_0^1 f(x)g(x)dx$$

A collection of linearly independent functions $\psi_i^j(x)$ spanning W^j are called wavelets, W^j being the new vector space and the orthogonal compliment of V^j in V^{j+1}. W^j represents the space of all functions in V^{j+1} that are orthogonal to all functions in V^j under the chosen inner product. Two important properties to note here is that the basis function ψ_i^j of W^j, together with the basis function $\varnothing_i^j$ of V^j form a basis for V^{j+1}, and every basis function ψ_i^j of W^j is orthogonal to every basis function $\varnothing_i^j$ of V^j under the chosen inner product.

Like the scaling functions, the wavelets corresponding to the box basis are known as the Haar wavelets. This is given by

$$\psi_i^j(x) := \psi(2^j x - 1), \quad i = 0, \ldots, 2^j - 1,$$

where

$$\psi(x) := \begin{cases} 1 & \text{for } 0 \le x < 1/2 \\ -1 & \text{for } 1/2 \le x < 1 \\ 0 & otherwise \end{cases}$$

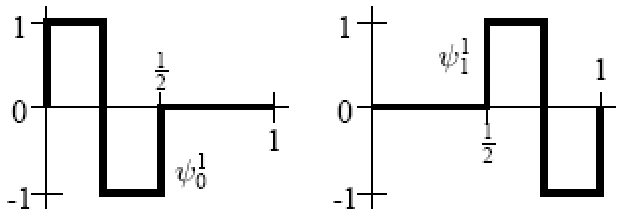
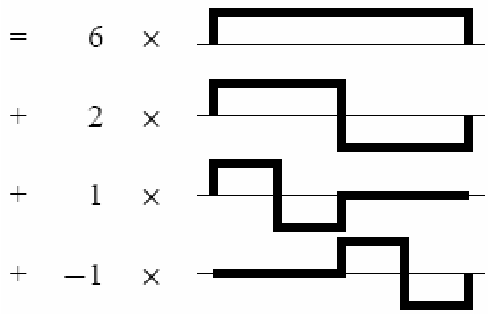


Figure 3-2. The two Haar wavelets spanning W^j.

$I(x)$can be expressed in terms of basis functions using pairwise averaging and differencing. Finally we can write the original image $I(x)$as a sum of basis functions in V^0, W^0, and W^1:

$$I(x) = c_0^0 \varnothing_0^0(x) + d_0^0 \psi_0^0(x) + d_0^1 \psi_0^1(x) + d_1^1 \psi_1^1(x)$$



The four coefficients [6 2 1 −1], are the Haar wavelet transform of the original image. Instead of using the box functions, $\varnothing_0^0, \psi_0^0, \psi_0^1,$ and ψ_1^1 have been used to represent the overall average, the broad detail, and the two types of finer detail possible in a function in V^2.

b). Haar wavelets in two dimensions

Wavelet decomposition of the pixel values in a two dimensional image takes place in two ways; standard decomposition (rectangular decomposition), and nonstandard decomposition (square decomposition). The standard decomposition of an image is achieved by first applying the one-dimensional wavelet transform to each row of pixel values. This results in an average value along with detailed coefficients for each row. Next, these transformed rows are treated as if they were themselves an image and apply the one-dimensional transform to each column. The resulting values are all detail coefficients except for a single overall average coefficient.

The second type, nonstandard decomposition, alternates between operations on rows and columns. We perform one step of horizontal pairwise averaging and differencing on the pixel values in each row of the image. Then, we apply vertical pairwise averaging and differencing to each column of the result. For a complete transformation, this process is repeated recursively only on the quadrant containing averages in both directions.

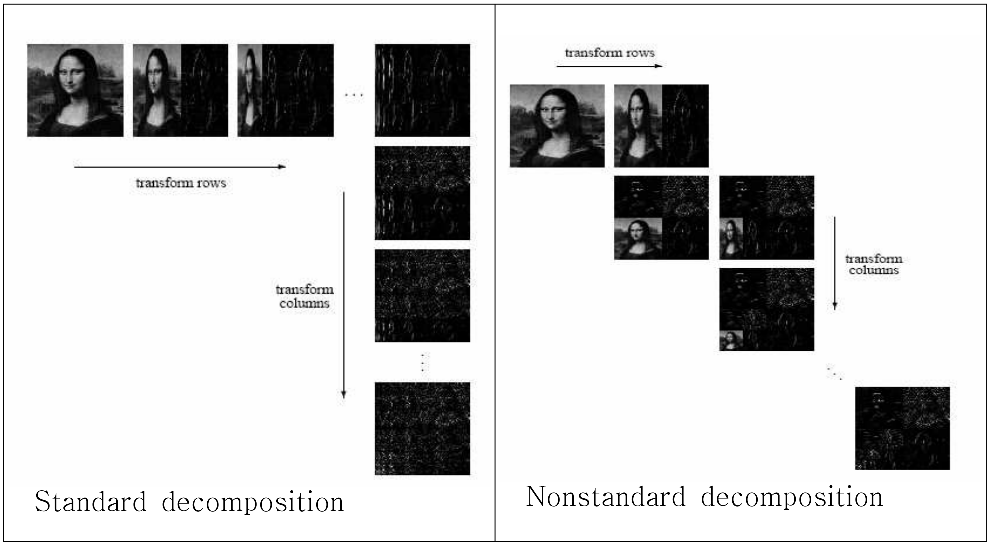


Figure 3-3 shows standard and nonstandard decomposition in Haar wavelet.

C. Wavelet Packet Analysis overview

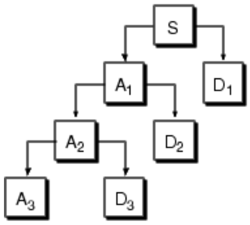
Wavelet transform is a new way to represent signals by localizing them in both time domain and frequency domain. In wavelet analysis, a signal can be split into the low-passed (approximation) signal and the high-passed (detail) signal. The detail signals which contain most of the clutter information are then thresholded to remove clutters. The approximations and the modified details are reconstructed using inverse wavelet transform to get a modified signal with reduced background clutter and nearly unchanged targets. Wavelet Packet Analysis has a feature known as "best-tree", a wavelet shrinkage method that yields high clutter suppression. Many approaches can be used to clutter suppression using wavelet analysis. These are categorized into two fundamental groups: clutter suppression in the discrete wavelet transform domain and in the continuous wavelet transform domain. Because of the best-tree factor, the wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. Compression and De-noising ideas developed in the wavelet framework are exactly the same in wavelet packet framework with the difference in wavelet packet's complexity and flexibility analysis as been mentioned above (splitting of both details and approximations). De-noising and compression procedures are two interesting application of wavelet packet analysis and involves four steps:

1. Decomposition
2. Computation of the best-tree
3. Thresholding of the wavelet packet coefficients
4. Reconstruction

In this paper, we propose the use of details obtained from the decomposition to segment a page and classify the regions of interest appropriately. The decomposed details of the wavelet packets has a lot more detailed features and more distinct than just using multi-resolution wavelet methods like Haar's wavelet or many others. To expound on the above mentioned steps: the decomposition here means that approximation coefficients are split into two parts; the approximation coefficients and the detail coefficients. The approximation signal from the previous stage is then split recursively into a next-level approximation and detail. This process may lead to loss of information between the successive approximations. The lost information is captured in the detail coefficient. The next step consists of splitting the new approximation coefficient vector; successive details are never re-analyzed. The wavelet analysis and the wavelet packet analysis are similar in principle but in the corresponding wavelet packet situation, each detail coefficient vector is also decomposed into two parts using the same approach as in approximation vector splitting. The decomposition is primarily to start from a scale-oriented decomposition and then analyze the obtained signals of frequency subbands. From the generated best-tree in the wavelet packet analysis, a suitable wavelet packet that best represents the feature of the clutter is used to perform the wavelet packet transform of the input signal.

It is noted here that the wavelet packet analysis is also recursive. That is, each newly computed wavelet packet coefficient sequence becomes the root of its own analysis tree. This recursive nature yields different ways to encode the signal if we apply the wavelet packet transform n times, n being the number of levels of decomposition. The result is the wavelet decomposition tree. From this very big and vast decomposition tree, how can we choose one of all these possible encoding? This presents an interesting problem in our wavelet analysis world.

This stage brings us to the local energy estimation. The local energy estimate is utilized for the purpose of identifying areas in each channel (subband), where the band pass frequency components are strong resulting in a high energy value and the areas where it is weak into a low energy value. At this step we need to estimate the energy of the filter responses in a local region around each pixel. Local energy estimation does this through several nonlinear operators namely magnitude operation, average absolute deviation and standard deviation.



$$
\begin{aligned}
S &= A_1 + D_1 \\
&= A_2 + D_2 + D_1 \\
&= A_3 + D_3 + D_2 + D_1
\end{aligned}
$$

Figure 3-4 shows ordinary wavelet decomposition tree

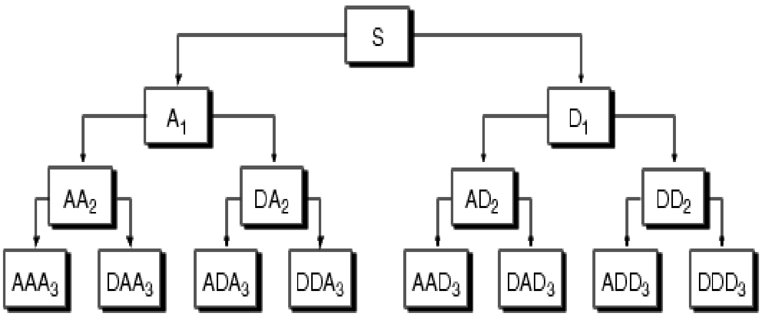


Figure 3-5 shows wavelet packet decomposition tree

Figure 3-4 shows an ordinary wavelet decomposition with the representation of the signal as

$$S = A_3 + D_3 + D_2 + D_1$$

where S is the original signal, A is approximation and D for details.

The subscripts indicate the level of decomposition e. g. A_3 shows approximation at level 3, D_3 shows detail at level 3 and so on. As you might have realized, for an n-level decomposition wavelet analysis, there are $n + 1$ possible ways to decompose or encode the signal.

Figure 3-5 shows the details as well as approximations being split and almost all the nodes become parent nodes except for the terminal nodes. Wavelet packet decomposition tree yields more than $2^{2^{n-1}}$ different ways to encode the signal. This complete binary tree includes the wavelet decomposition tree and many other detailed features which are very essential in signal processing. A signal S, in wavelet packet analysis, can be represented as $A_1 + AAD_3 + DAD_3 + DD_2$. This kind of representation is not possible with ordinary wavelet analysis.

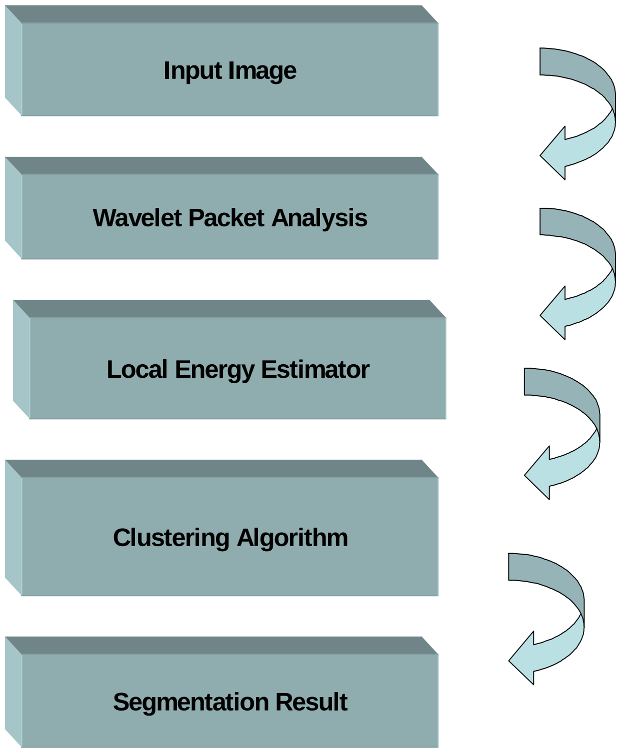


Figure 3-6. Document Image Segmentation Algorithm

D. Text / Non-text Segmentation Algorithm

a). Wavelet Packet Analysis

As been mentioned above, the wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. The methods of wavelet packets, which are a generalization of orthonormal and compactly supported wavelets, have been successfully used for data compression. Wavelet packet may be described by the collection of functions $\{ W_j(x) \mid j \in Z^+ \}$ obtained from

$$2^{\frac{p-1}{2}} W_{2n}(2^{p-1}x-l) = \sum_m h_{m-2l} 2^{\frac{p}{2}} W_n(2^p x - m) \qquad (1)$$

$$2^{\frac{p-1}{2}} W_{2n+1}(2^{p-1}x-l) = \sum_m g_{m-2l} 2^{\frac{p}{2}} W_n(2^p x - m) \qquad (2)$$

where p is a scale index, l is a translation index, $W_0(x) = \varnothing(x), W_1(x) = \psi(x), \varnothing(x)$ is a scaling function and j(x) is a basic wavelet. The discrete filters h_k and g_k are quadrature mirror filters [21, 22].

We can show that such wavelet packets are orthonormal in $L^2(R)$ and are well localized in both time and frequency. The inverse relationship between wavelet packets of different scales can be shown by,

$$2^{\frac{p}{2}} W_n(2^p x - k) = \sum_l h_{k-2l} 2^{\frac{p-1}{2}} W_{2n}(2^{p-1}x - 1) \qquad (3)$$
$$+ \sum_l g_{k-2l} 2^{\frac{p-1}{2}} W_{2n+1}(2^{p-1}x - 1).$$

As with Fourier methods, any function $f(x)$ 2 $L^2(R)$ can be decomposed into a wavelet packet basis. The coefficients of this decomposition are simply the inner products of f(x) with distinct wavelet packets. For example, coefficients from the inner product

$< f(x), W_n (2^p x - k) >$ indicates the intensity of this component in $f(x)$.

An approximation of an original function $f(x)$ using wavelet packet W_n at scale 2^p can be written as,

$$A_n^{2p} f(x) = \sum_k S^p_{n,k} 2^{\frac{p}{2}} W_n (2^p x - k) \qquad (4)$$

where

$$S^p_{n,k} = 2^{\frac{p}{2}} \int_{-\infty}^{\infty} f(x) W_n (2^p x - k) dx \qquad (5)$$

Here, we will show how wavelet packets may be computed efficiently. The following formula is derived from equation (3).

$$S^p_{n,k} = \sum_l h_{k-2l} S^{p-1}_{2n,l} + \sum_l g_{k-2l} S^{p-1}_{2n+1,l} \qquad (6)$$

Coefficients at coarser scales can be calculated using equations (1) and (2) as shown in the equations,

$$S^{p-1}_{2n,l} = \sum_m h_{m-2l} S^p_{n,m} \qquad (7)$$

$$S^{p-1}_{2n+1,l} = \sum_m g_{m-2l} S^p_{n,m} \tag{8}$$

For standard wavelet decomposition, only two wavelet packets W_0 and W_1 are used.

In this case, the index n is restricted to n = 0, and only nodes S^p_0 are decomposed from the equations (7) and (8) above. Thus only the leftmost node at each level has children, and each level has exactly two nodes. Therefore, from the subband filtering point of view, the difference between a wavelet packet decomposition and the standard wavelet transform is that the former recursively decomposes the high frequency components, thus constructing a tree structured multiband extension of the wavelet transform. In case of discrete signals, the original discrete signal is treated as the set of wavelet packet coefficients at the first scale (p = 0), and then the same procedure explained above is followed.

The basis functions are obtained by translation and scale change. They remain well localized in both time and frequency domains and represent scale and spatial information. Thus a complete tree presents the distribution of a signal within a scale space continuum. The total number of coefficients in a complete tree decomposition is exactly equal to the number of points (pixels) in an original signal. Energy distribution within transform spaces have been applied in Fourier analysis [23]. There is a similar significance in wavelet packet analysis. Since wavelet packets form orthogonal bases, their decompositions will preserve energy. It is easy to show that

$$\sum_k (S^p_{n,k})^2 = \sum_l (S^{p-1}_{2n,l})^2 + \sum_l (S^{p-1}_{2n+1,l})^2 \tag{9}$$

Therefore, if we define a energy measure as $E_n^p = \sum k(S_{n,k}^p)^2$, then

$$E_n^p = E_{2n}^{p-1} + E_{2n+1}^{p-1} \tag{10}$$

The first step here is to compute the energy associated within each wavelet packet. We then hypothesized that the energy pattern distributed in scale space shall provide unique information, and support a representation for classification. The representation, which we also call signature, is considered a feature vector consisting of a set of energy values. The study showed that such signatures can provide a powerful and efficient means to accomplish signal classification.

b). Entropy

This also is another alternative measure of information. It is defined by,

$$H(x) = -\sum_k |x_k|^2 \log |x_k|^2 \tag{11}$$

Entropy was previously proposed in [24] for texture analysis, and has been used in [13] to identify a "best basis" for building wavelet packet libraries for signal compression. In this paper, we compare the entropy and energy measures described above for their performance in accomplishing robust texture discrimination. A special class of separable 2-D wavelet packets is used in case of 2-D signals extension. Here, the energy preserving equation is specified by the sum

$$E_{n,m}^p = E_{2n,2m}^{p-1} + E_{2n,2m+1}^{p-1} + E_{2n+1,2m}^{p-1} + E_{2n+1,2m+1}^{p-1} \tag{12}$$

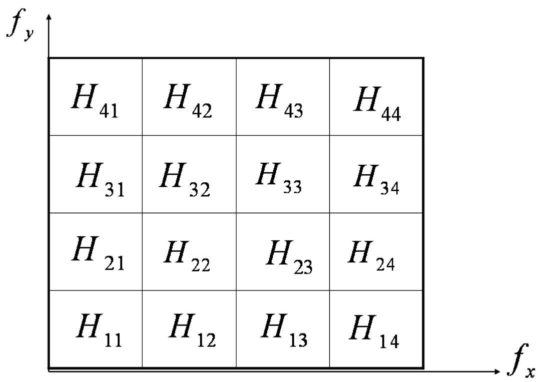
In the filtering step, orientation selectivity is embedded in the tensor product of the lowpass filter *h* and high-pass filter *g*, and therefore, energy distributions are captured in three subbands. Figure 3-7 below shows the wavelet packet transform for levels one and two. These filter outputs basically give a measure of signal energies at different directions and scales.

Figure 3-7; Wavelet packet decomposition image.

c). Multi-Level Decomposition

As explained above and in [25], the objective of the filtering is to find out about the discontinuities that exist within the image. Wavelet packet analysis, the feature extraction method that we have used has a multi-channel filtering. A filter bank is formed, which in essence is the set of bandpass filters with frequency and orientation selective properties. Figure 3-7 above shows the image whose edges have been detected using a 2-D filtering. Horizontal edges are detected by high-pass filtering on columns and low-pass filtering on rows; vertical edges are detected by low-pass filtering on the columns and high-pass filtering on the rows; diagonal edges are detected by high-pass filtering on columns and high-pass filtering on rows; horizontal-diagonal edges are detected by high-pass filtering on columns and low-pass filtering on rows; vertical-diagonal edges are detected by low-pass filtering on columns and high-pass filtering on rows.

The channels are a combination of high frequency components according to different directions. The wavelet packet decomposition image shown in Fig.3-7 displayed on x-y axis takes the form of the figure below;



The above wavelet packet decomposition image is shown below how different subbands are formed from the input image into individual features extracted on different directions.

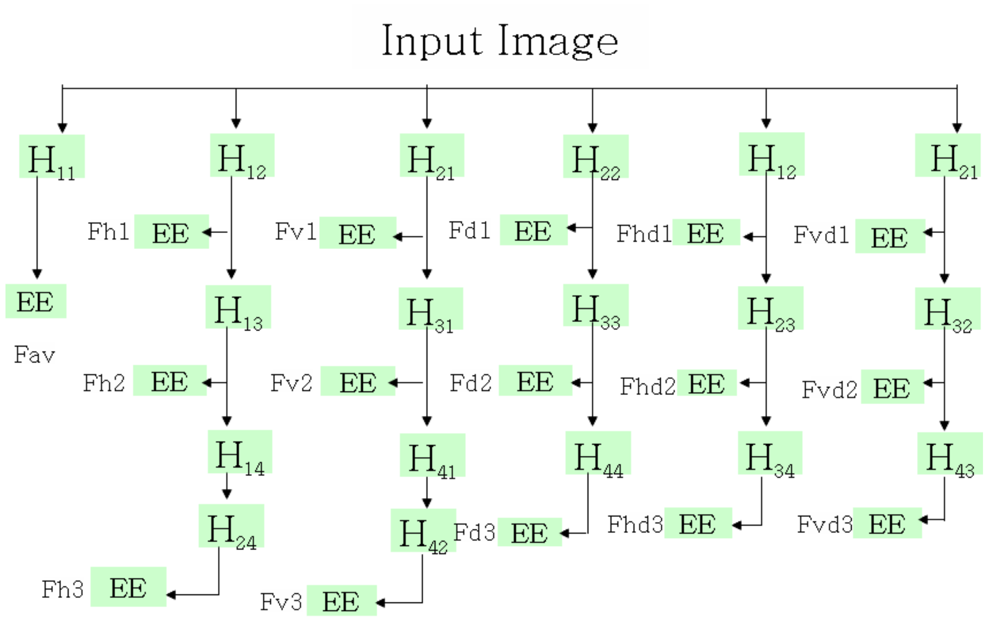


Figure 3-8. Basic decomposition scheme of our algorithm.

H – High frequency components on columns and rows **EE** – Local energy estimation which is summation of nonlinear operator and Gaussian blurring **F** – feature, average(*av*), horizontal(*h*), vertical(*v*), and diagonal(*d*)

Here we show the combination subband by subband.

Horizontal Direction

$filt_{h1} = H_{12}$

$filt_{h2} = H_{12} + H_{13}$

$filt_{h3} = H_{12} + H_{13} + H_{14} + H_{24}$

Vertical Direction

$filt_{v1} = H_{21}$

$filt_{v2} = H_{21} + H_{31}$

$filt_{v3} = H_{21} + H_{31} + H_{41} + H_{42}$

Diagonal Direction

$filt_{d1} = H_{22}$

$filt_{d2} = H_{22} + H_{33}$

$filt_{d3} = H_{22} + H_{33} + H_{44}$

Horizontal - diagonal direction

$filt_{hd1} = H_{12}$

$filt_{hd2} = H_{12} + H_{23}$

$filt_{hd3} = H_{12} + H_{23} + H_{34}$

Vertical - diagonal

$filt_{vd1} = H_{21}$

$filt_{vd2} = H_{21} + H_{32}$

$filt_{vd3} = H_{21} + H_{32} + H_{43}$

d) Local energy estimation

Local energy estimation is the next step with the task to estimate the energy of the filter responses in a local region around each pixel. It is utilized for the purpose of transmitting areas in each channel where the bandpass frequency components are strong resulting in a high energy value (constant gray level) and the areas where it is weak into a low energy value. Two dimensional Haar wavelet packet is used to characterize the local energy values of pixels. Haar wavelet packet analysis has not only rather good performance to characterize texture features but also its computation is efficient. In (8) above, orientation selectivity in the tensor product of low-pass filter h and high-pass filter g is considered. In each scale level, the image is decomposed into four subbands: LL, LH, HL, and HH. On the horizontal and vertical scale, LL means the horizontal low-frequency and vertical low-frequency of the image, LH stands for horizontal low-frequency and vertical high-frequency, HL the horizontal high-frequency and vertical low-frequency, and finally HH which represent horizontal high-frequency and vertical high-frequency decomposition of the image. In three of the subbands, high-pass filter have been detected. It is these three high-frequent subbands that we adopt for the extraction of local text / non-text features. The addition of high-frequent coefficients in the $k-th$ scale level is given by, $h_{k_i} = LH_k + HL_k + HH_k$, where $k = 1,\ldots,L$

Although energy is usually defined in terms of a squaring nonlinearity, in a generalized energy function, however, other alternatives are also available for use. We have studied several nonlinear operators which include the magnitude operation, average absolute deviation and standard deviation calculated over small overlapping windows around each pixel.

The local energy $eng_{k_i}(x,y)$ around the x, yth pixel for several nonlinearities are formally given as follows:

magnitude operation

$$eng_{k_i}(x,y) = |h_{k_i}(m,n)|$$

average absolute deviation

$$eng_{k_i}(x,y) = \frac{1}{R}\sum_{m=1}^{w}\sum_{n=1}^{w}|(h_{k_i}(m,n) - \overline{h}_{k_i}(x,y))|$$

standard deviation

$$eng_k(x,y) = \sqrt{\frac{1}{R}\sum_{m=1}^{w}\sum_{n=1}^{w}\left|(h_{k_i}(m,n)^2 - \overline{h}_{k_i}(x,y)^2)\right|}$$

where w is the window size and R = w x w, while $\overline{h}_{k_i}(x,y)$ is the mean around the (x, y)th pixel and $h_{k_i}(x,y)$ is the filtered image. Experimentally, we have observed that the standard deviation over small overlapping windows around each pixel gives better performance than the other nonlinearities stated above. The reason being, it is independent of any parameter, i. e. independent of the dynamic range of the input image and also of the filter amplification.

To extract the text regions from the output of the decomposed image, we need to blur the text / non-text regions using Gaussian smoothing filter. The form is given in,

$$G(x,y) = \frac{1}{\sqrt[2\pi]{\sigma}} e^{\frac{1}{2\sigma^2}}(x^2 + y^2)$$

where σ determines the bandwidth of averaging window. Finally, we obtain the feature images corresponding to $h_{k_i} = LH_k + HL_k + HH_k$ by the means of Gaussian low-pass filtering. This is given by

$$F(x,y) = \frac{1}{W} \sum_{(m,n) \in W} |G(h_{k_i}(m,n))|$$

we adapt the W size from 9 x 9 and 15 x 15 to be appropriate in most of our experiment images corresponding to 256 x 256 and 512 x 512 respectively.

e). Unsupervised classifier

The next step having obtained the feature images is to integrate these feature images to achieve final segmentation. The scale-space is defined as the vector of features at different scales taken at a single pixel in an image.

Let us take for example that our image has a K texture categories present in it. Sometimes the texture features obtained are capable of discriminating between these K categories. In that case, the patterns belonging to each category will form a cluster in the feature space which is compact and isolated from clusters corresponding to other texture categories. There are such many pattern-clustering algorithms endowed with this task in ideal mode. These algorithms accept as input a set of features and then use consistent labeling for each pixel. Fundamentally, this can be considered a multidimensional data clustering problem. This paper is a two-class segmentation problem; we base our assumption that the text portion of the document image is comprised of one texture class and the non-text class of the other. A part from the unsupervised classifier, the other version of document image segmentation called supervised classifier would mean that the segmentation of the document is dependent on the knowledge of scale, scanning resolution, rotation, skewness, font size, type of layout, etc. Our aim in this paper is to make the segmentation scheme independent of all aforesaid issues and be robust, thus need for unsupervised classifier. We have chosen a traditional *k-means* algorithm for feature extraction part because of its many advantages over others. It is a simple method and labels each pixel independently without taking into account the high correlation between neighboring pixels.

k-means

To demonstrate how *k-means* work, we will use $(x[1{:}F,\ 1{:}S],\ K)$ for clarity.

x[1:Q, 1:S] represents the array of structure containing vectors

F to stand for the number of feature elements in a feature vector

S denotes the data size (number of pixels in the image) and

K the number of classes (number of clusters).

A pseudo program of *k-means* algorithm;

```
begin
      begin (Initialization)
         Select K number of vectors arbitrarily from the array
         x[1:F, 1:S] and then each of these are assigned a class,
         these form the initial class centers C_k's.
      end


begin
         Euclidean distance between each of the S vectors and
         selected K vectors are found out taking one out of
         S vectors at a time. A vector is assigned to the class k
         if it is closest to C_k. Recompute the class centers C_k
         taking mean of the vectors assigned to class k.
         Repeat until there is no change in the class centers.
      end
end
```

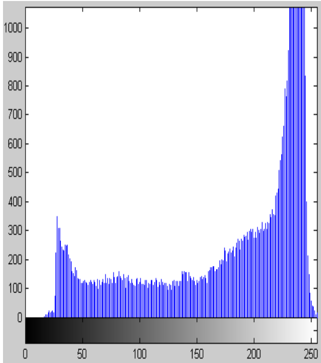
IV. Experimental Result

Several documents images are analyzed using our method, so as to demonstrate the performance of our algorithm. These document images are scanned from Korean newspapers and journals. In these experiments, we have taken into account those subbands which have the highest values of energies, meaning that these subbands would supply more information of text than the others.

We have tested 100 images, in which Korean texts appear in them. Most of texts are aligned horizontally but there are some aligned vertically. Some characters are laid over simple background. However, there are still a lot of characters laid over complex background. By experiments, we found that the contrast of characters with their local background extends a wide range in some images.

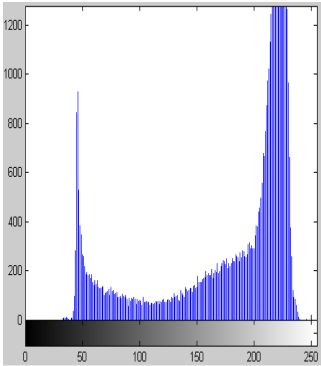
Table 4-1. Test images and results

Test Images	Image Size	Mean	Standard Deviation	Median Value
(a) paper1	256×256	181.70	68.09	213
(b) paper2	256×256	181.82	58.35	212
(c) paper3	256×256	225.69	48.24	254
(d) paper4	256 x 256	159.27	47.40	168
(e) paper5	256 x 256	203.92	43.86	220
(f) paper6	256 x 256	179.82	44.16	197

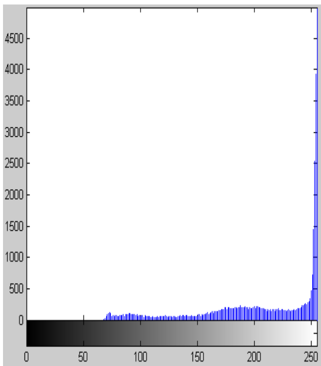


(a) paper1

"밤이 싫어, 밤이 싫어 가로등 꺼진 밤 교정이 싫어"

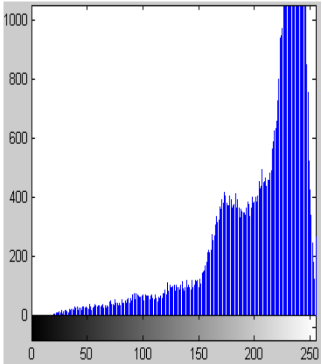


(b) paper2



(c) paper3


Milton Friedman, Freedom Fighter



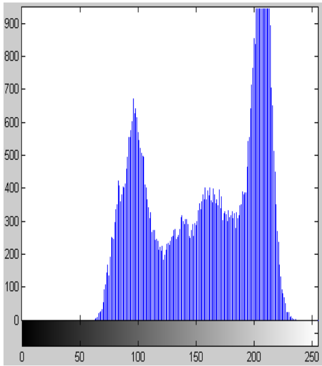
(d) paper4


The Korea Herald

Chaebol real estate holdings surge

Probe co despite d from Lo

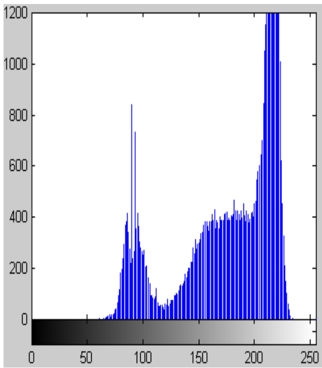
Han grilled by lawmakers



(e) paper5

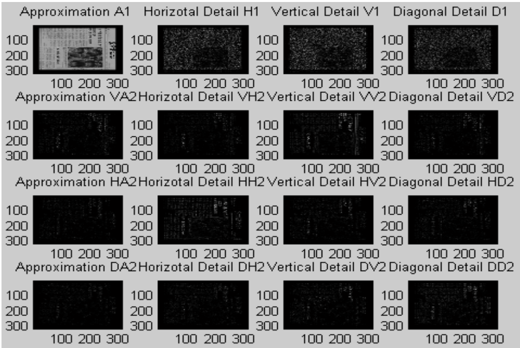

ENTERTAINMENT

'Pitt, Jolie mull Namibian baby name'

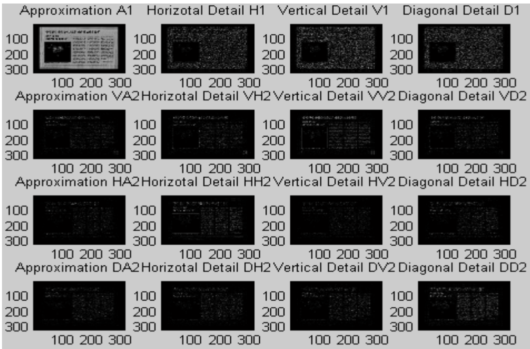


(f) paper6

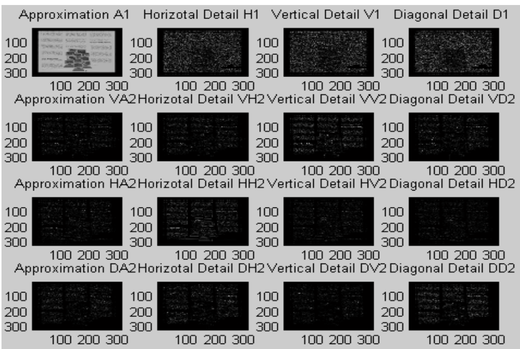
Figure 4 – 1. Original images and histograms


Approximation A1
Horizotal Detail H1
Vertical Detail V1
Diagonal Detail D1
Approximation VA2
Horizotal Detail VH2
Vertical Detail VV2
Diagonal Detail VD2
Approximation HA2
Horizotal Detail HH2
Vertical Detail HV2
Diagonal Detail HD2
Approximation DA2
Horizotal Detail DH2
Vertical Detail DV2
Diagonal Detail DD2

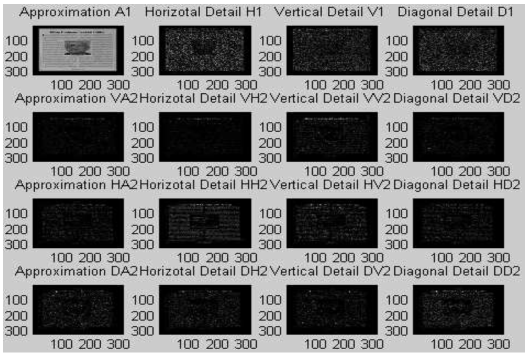
(a)


Approximation A1
Horizotal Detail H1
Vertical Detail V1
Diagonal Detail D1
Approximation VA2
Horizotal Detail VH2
Vertical Detail VV2
Diagonal Detail VD2
Approximation HA2
Horizotal Detail HH2
Vertical Detail HV2
Diagonal Detail HD2
Approximation DA2
Horizotal Detail DH2
Vertical Detail DV2
Diagonal Detail DD2

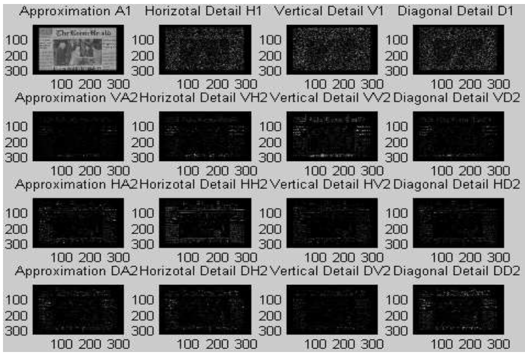
(b)


Approximation A1
Horizotal Detail H1
Vertical Detail V1
Diagonal Detail D1
Approximation VA2
Horizotal Detail VH2
Vertical Detail VV2
Diagonal Detail VD2
Approximation HA2
Horizotal Detail HH2
Vertical Detail HV2
Diagonal Detail HD2
Approximation DA2
Horizotal Detail DH2
Vertical Detail DV2
Diagonal Detail DD2

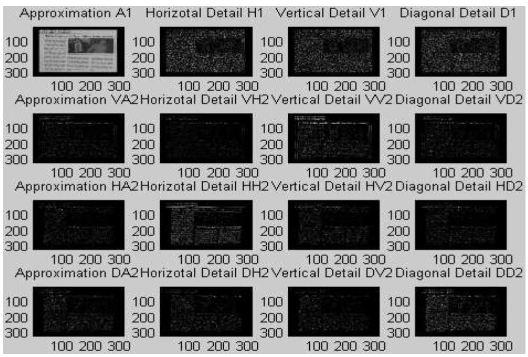
(c)


Approximation A1
Horizotal Detail H1
Vertical Detail V1
Diagonal Detail D1
Approximation VA2
Horizotal Detail VH2
Vertical Detail VV2
Diagonal Detail VD2
Approximation HA2
Horizotal Detail HH2
Vertical Detail HV2
Diagonal Detail HD2
Approximation DA2
Horizotal Detail DH2
Vertical Detail DV2
Diagonal Detail DD2

(d)

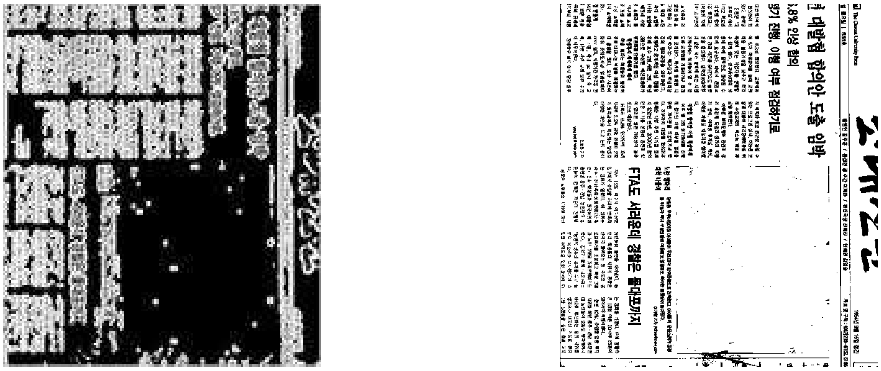

Approximation A1
Horizotal Detail H1
Vertical Detail V1
Diagonal Detail D1
Approximation VA2
Horizotal Detail VH2
Vertical Detail VV2
Diagonal Detail VD2
Approximation HA2
Horizotal Detail HH2
Vertical Detail HV2
Diagonal Detail HD2
Approximation DA2
Horizotal Detail DH2
Vertical Detail DV2
Diagonal Detail DD2

(e)

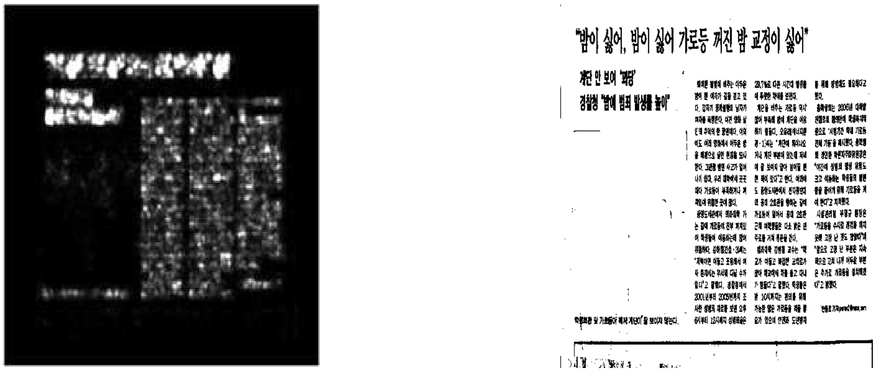

Approximation A1
Horizotal Detail H1
Vertical Detail V1
Diagonal Detail D1
Approximation VA2
Horizotal Detail VH2
Vertical Detail VV2
Diagonal Detail VD2
Approximation HA2
Horizotal Detail HH2
Vertical Detail HV2
Diagonal Detail HD2
Approximation DA2
Horizotal Detail DH2
Vertical Detail DV2
Diagonal Detail DD2

(f)

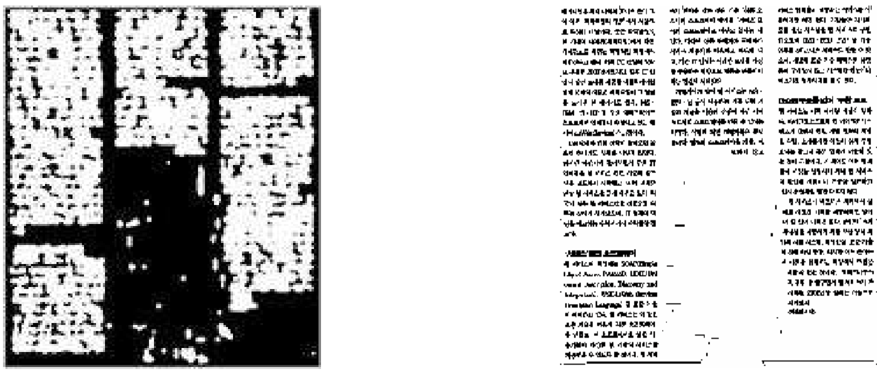
Figure 4 - 2. Wavelet Packet Analysis



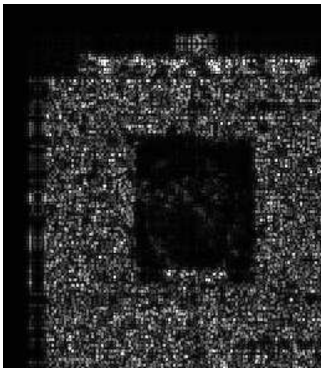
(a) paper1

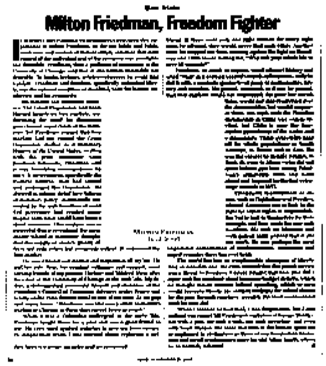


(b) paper2



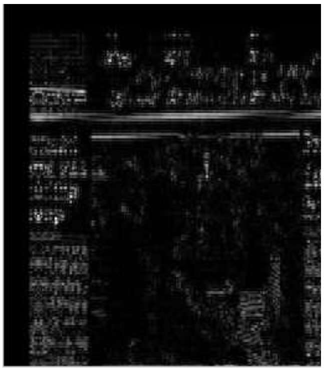
(c) paper3





Milton Friedman, Freedom Fighter

(d) paper5



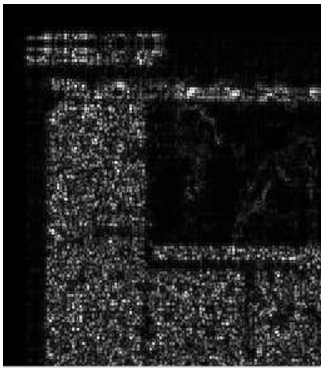
The Korea Herald

Chaebol real estate holdings surge

Probe co despite c from Lo

Han grilled by lawmakers

(e) paper6



ENTERTAINMENT

'Pitt, Jolie mull Namibian baby name'

(f) paper7

Figure 4 – 3. Feature images and result images

V. Conclusion

The importance of separating text part from the graphic part in documents has become inevitable in this digitalization era. Efficient and easy access of these documents via computers and networks is an important task that researchers must achieve. In this work we presented a new technique for segmenting the text from nontext part based on textural features using wavelet packet analysis. The decomposition gives a multiscale multidirectional representation of the image and yields a large number of subbands. These multidirectional features depends on the level of decomposition and provides a wide range of best selection features and requires no downsampling. On the decomposed subbands, we used local energy estimator over small overlapping windows around each pixel and *k-means* clustering algorithm to detect and separate the text / nontext parts of the image. Our method, wavelet packet analysis, did not assume any a priori knowledge about the size of the font size, scanning resolution, column layout, orientation and may other constraints of the input image. Skewness that most traditional methods fail to properly classify was solved by our method. This shows that our method is purely unsupervised. This can further be supported by our many experiments carried on both structured and unstructured images with the results as been shown. Most computations take place at the filtering and feature extraction operations; nonetheless, it is still very simple, computationally less expensive, and efficient. Future work will be more focused on extraction and separation of text from non-text on a complex document images and natural scenes.

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논문제목	한글 : 웨이블릿패킷분석을 이용한 문서영상에서의 텍스트/비텍스트 검출 방법				
	영어 : A Text / Non-text Detection Method in Document Image using Wavelet Packet Analysis				

본인이 저작한 위의 저작물에 대하여 다음과 같은 조건아래 조선대학교가 저작물을 이용할 수 있도록 허락하고 동의합니다.

- 다 음 -

1. 저작물의 DB구축 및 인터넷을 포함한 정보통신망에의 공개를 위한 저작물의 복제, 기억장치에의 저장, 전송 등을 허락함
2. 위의 목적을 위하여 필요한 범위 내에서의 편집・형식상의 변경을 허락함. 다만, 저작물의 내용변경은 금지함.
3. 배포・전송된 저작물의 영리적 목적을 위한 복제, 저장, 전송 등은 금지함.
4. 저작물에 대한 이용기간은 5년으로 하고, 기간종료 3개월 이내에 별도의 의사 표시가 없을 경우에는 저작물의 이용기간을 계속 연장함.
5. 해당 저작물의 저작권을 타인에게 양도하거나 또는 출판을 허락을 하였을 경우에는 1개월 이내에 대학에 이를 통보함.
6. 조선대학교는 저작물의 이용허락 이후 해당 저작물로 인하여 발생하는 타인에 의한 권리 침해에 대하여 일체의 법적 책임을 지지 않음
7. 소속대학의 협정기관에 저작물의 제공 및 인터넷 등 정보통신망을 이용한 저작물의 전송・출력을 허락함.

동의여부 : 동의(√) 반대( )

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