

## Image Enhancement Through Local Segmentation and Denoising



### Engineering

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### ABSTRACT

*A unifying philosophy for carrying out low level image processing called local segmentation is presented here. Local segmentation provides a way to examine and understand existing algorithms, as well as an idea for creating new algorithms. Local segmentation can be apply to variety of important image processing jobs. The minimum message length (MML) information is used to select between models having different structure and complexity in an effort to improve the local segmentation. This leads to advance improvements in denoising performance. It is supposed that image processing in common could benefit greatly from the use of the local segmentation methodology.*

### II. Introduction

Image processing is a rapidly growing area of computer science. Its growth has been fuelled by technological advances in digital imaging, computer processors and mass storage space devices. Fields which usually used analog imaging are now switching to digital systems, for their usefulness and adoptability. Significant examples are medicine, silver screen and videography, photography, remote sensing, and security monitoring. These and other sources produce huge amount of digital image data every time, most of them could ever be examined manually.

Digital image processing is concerned mainly with extracting useful information from image files. Ideally, this is processed by computers, with slight or no human intervention. Image processing algorithms may be positioned at three levels. Techniques which deal immediately with the raw, probably noisy pixel values, with denoising and edge detection being good examples are at the lowest level. Algorithms which employ low level results for further means, such as segmentation process and edge linking are at the middle level. Methods which attempt to extract semantic meaning from the information provided by the lower levels, for example, handwriting recognition are at the highest level.

The literature abounds with algorithms for achieving various image processing tasks. This aim of this paper is a unified approach to low level image processing called local segmentation

### III. Local Segmentation

The local segmentation principle states that the first step in processing a pixel should be to segment explicitly the local region around it. On the basis of local scale, it is easier to clear which pixels belong together, and which pixels don't. Segmentation procedure results in a local approximation of the core image; it can successfully separate the noise from the signal. Thus signal is operated directly by the higher level algorithms without any risk about amplification of the noise. Local segmentation can provide a common framework for the construction image processing algorithms.

Image denoising is mainly a suitable process to demonstration of the application of local segmentation.

### IV. Denoising

Denoising is the process of removing unwanted noise of the core image. A denoised image is an approximate figure to the basic true image, before its contamination. A high-quality denoising algorithm must concurrently preserve structure of the basic image as well as remove noise from it. It is Obvious; to do this task the algorithm must be capable to recognize what structure is present. Specifically, Local segmentation attempts to disconnect structure from noise signals on a basis of local

scale. Therefore denoising would be a fine application with which it is to test unlike approaches to local segmentation. Local regions just include a small number of pixels. It is unlikely that there would be more than a few segments present at this type of scale, so separate, uniform groups of pixels are likely to be a part of the same global segment section. Conventional segmentation based on threshold techniques, such as k-means, perform well with this type of data. This technique can be used to develop FUELS method that is an algorithm for denoising greyscale images which is affected by additive noise. FUELS needs only one parameter that is the noise variance, this parameter can be supplied by the user or estimated from the image automatically. This noise variance and pixel values are used by a model order selection standard for finding the best number of segments there in the local region.

### V. Local segmentation in image processing

The local segmentation principle states that the first step in processing a pixel should be to segment the local region encompassing that pixel. This provides a snapshot of the local structural features of the image, with the signal clearly separated from the noise. It is hoped that the identified structural information could be used to implement many image processing tasks including, but not limited to, image denoising [1], pixel classification [2], edge detection [3], and pixel interpolation [4].

Global segmentation is concerned with segmenting a whole image. Local segmentation deals with segmenting sub-images which are small windows on a whole image. Although a sub image is still a valid image, it is also a fragment of a larger scene being processed in isolation. A side-effect of this is shown in Figure 1.1. The image consists of two global segments: a light cross on a dark background. Each of the segments is homogeneous and fully connected. The sub-image is also a cross on a background, but its background consists of four spatially disjoint pixels. Without a larger context it is difficult to ascertain whether they should be treated as one or four segments. A clustering algorithm, guided only by pixel intensities, would group them into a single segment.

The number of pixels available to local segmentation is much lower than what most global segmentation algorithms would expect. This has an effect on the typical number of distinct segments expected to be encountered. Figure 1.2 a is a typical greyscale image called lena. Figure 1.2 b shows an image which plots, for each pixel from lena, the standard deviation of the sub-image centered on that pixel. The standard deviations range from 0 to 72, and are represented here using intensities from black to white.

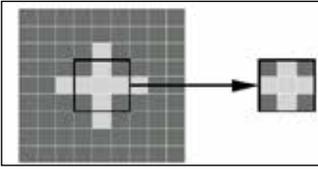
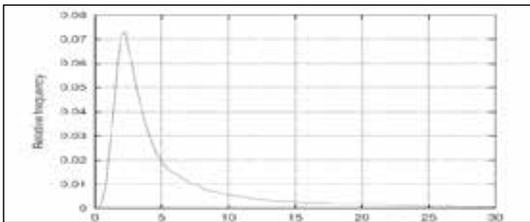


Figure 1.1 A sub-image taken from the centre of a image with two segments.



Figure 1.2:(a)original image (b)local 3x3 standard deviations, with black representing 0 and white 72.

Homogeneous regions in the original image produce dark areas in the standard deviation image, while edges are responsible for lighter areas. The majority of Figure 1.2 b is dark. Figure 2 shows a histogram of the standard deviations, which is expected to be unimodal and skewed to the right [6]. The peak at 2.4 corresponds roughly to the natural level of variation within homogeneous regions. The skew toward larger standard deviations is caused by heterogeneous edge and texture regions varying above the natural level.



Local standard deviation

Figure 2 : Histogram of local standard deviations shown in Figure 1.2.b

The area under the histogram near the natural level of variation is much higher than in the skewed. Thus it suggests that it is extremely likely that a randomly selected sub-image will be homogeneous, consisting of a single segment. This is in stark contrast to global segmentation, where the diagnosis or even consideration of a single segment result is rare. A local segmentation algorithm must therefore be able to determine automatically the number of segments present in the sub-image. Fortunately, this task is made easier because the number of segments is likely to be small.

A small sub-image implies small segments. Global segmentation algorithms, in an attempt to reduce over-segmentation, often disallow segments containing less than a specified number of pixels. A local segmentation algorithm should expect to diagnose many small segments, including those consisting of a single pixel

The “K- means algorithm for Local Segmentation:

1. Choose Initial class means.
2. Assign each pixel to the class with the closest mean.
3. Reassign one pixel to a new class such that the move best reduces the overall sum of square distances criterion.
4. Recompute the class means using the new assignments.
5. If the criterion was better, return to Step 3.

VI. FUELS METHOD for denoising & COMPARIION to OTH-

ER DENOISING METHOD

The local segmentation principle may be used to develop a variety of low level image processing algorithms. In this paper it will be applied to the specific problem of denoising greyscale images contaminated by additive noise. The best image denoising techniques attempt to preserve image structure as well as remove noise. This problem domain is well suited to demonstrating the utility of the local segmentation philosophy. The denoising algorithm presented is called FUELS, which stands for filtering using explicit local segmentation. FUELS differs from existing local denoising methods in various ways. The local segmentation process clearly decides which pixels belong together, and does so democratically, without using the centre pixel as a reference value. If the computed local approximation suggests changing a pixel’s value by too much, the approximation is ignored, and the pixel is passed through unmodified. The fact that each local approximation overlaps with its neighbour means that there are multiple estimates for the true value of each pixel. By combining these overlapping estimates, denoising performance is further increased.

It has been shown that the principles of local segmentation can be used to develop effective denoising algorithms. After many analyses, the FUELS algorithm for denoising greyscale images contaminated by additive noise was presented. FUELS has an efficient implementation, and only requires one parameter, the level of noise in the image. This can be supplied by the user, or FUELS can determine it automatically.

The RMSE was used to measure objectively the closeness of denoised images to the originals. FUELS consistently produced lower RMSE results than SUSAN [7], the next best performer. The WCAE was used to gauge the worst case performance of each algorithm. FUELS had the desirable attribute of having a WCAE proportional to the noise level in the image. The others, SUSAN included, tended to have constant or erratic WCAEs. To assess the structure preserving ability of each algorithm, difference images were used to highlight those areas of the image in which larger errors occurred. Although structure was apparent in all the difference images, FUELS’ tended to contain the least. The FUELS algorithm has various attributes which are responsible for its good performance.

Example: The lenna image [5] in Figure 1.2 a is the single most popular test image used by the image processing community. Because lenna is not synthetic, it already contains some noise of unknown distribution. Under the assumption of additive Gaussian noise, the natural noise standard deviation,  $\sigma$ , was estimated as being somewhere between 2 and 3. Using the original lenna as ground truth is difficult, because any good denoising algorithm will remove both the original and synthetic noise. As the added noise level,  $\sigma$ , increases, the original noise is swamped and hence can mostly be ignored.

Figure 3 plots RMSE results for lenna. Although FUELS performs best at all noise levels, the two SUSAN variants are very close.

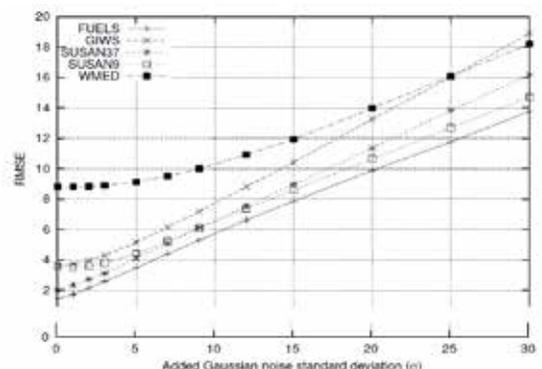


Figure 3

## VII. CONCLUSION

The work on FUELS introduced the idea of 'do no harm' (DNH). FUELS creates two candidate models, and chooses the one it thinks is better. It is possible that both candidates

are poor ones for the local region, so using one could do more damage than good. If this situation was identified by the DNH mode, the pixels were left unmodified. This is similar

to defaulting to a null model if there is insufficient evidence for any of the alternatives. The DNH (DO NO harm) idea is not particular to FUELS or even local segmentation. It could be applied to any denoising algorithm to improve its worst case performance, especially at low noise levels.

Most denoising algorithms use the centre pixel of the window as a reference pixel to compare with each other pixel in turn, to produce a denoised estimate of the centre pixel only. Local segmentation differs from this in that it treats all pixels in the window democratically, producing denoised values for them all. Because windows overlap, there are multiple estimates for each pixel. With little extra work, FUELS was able to average these estimates to further improve performance. This illustrates the advantages of combining predictions from different experts, which is harder to do when the centre pixel receives special treatment.

### MML (Minimum Message Length)

MML proposes that, for each model being considered, a two part message containing a description of the model and the data given that model be constructed. The message having the shortest overall message length is considered to contain the best model for the data. Each message must be constructed in such a way that it can be decoded by a receiver given only the same prior knowledge. That is, the message must be a lossless encoding of the data.

The MML[8] methodology was applied to local segmentation. The simple mean separation criterion used by FUELS was replaced by a message length comparison between candidate models. Each message was a concise, decodable encoding of the noisy pixels. The message with the shortest length was deemed

to contain the most appropriate model for the local region. By using MML, the arbitrary constant,  $H$ , that FUELS required, was eliminated. This introduced the possibility of diagnosing the presence of two segments with close, but distinct intensities. FUELS was incapable of this in very noisy images.

The FUELS denoising algorithm generates two candidate local segmentation models. It chooses what it considers to be the better one, and uses the resulting local approximation to estimate the underlying noiseless pixel values. It is a simple matter to replace the existing FUELS model selection criterion with the MML. Let the resulting denoising algorithm be called Pseudo-MML. This name has been chosen to avoid confusion when MML is applied differently later.

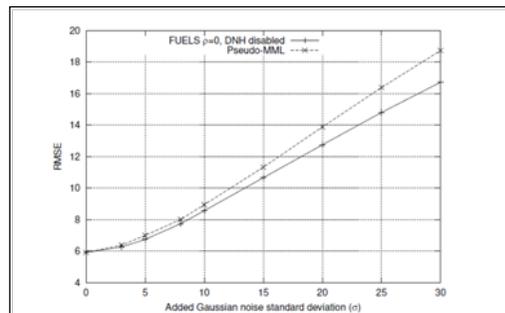


Figure 4 compares the RMSE performance of FUELS and Pseudo-MML for denoising montage. The true value of  $(\sigma)$  was given to both algorithms. Overlapping averaging and DNH were disabled, as the primary goal is to observe the effect of changing the model selection criterion. Pseudo-MML only considered the same two candidate models as FUELS.

Figure 4. RMSE comparison for denoising montage, true  $\sigma$  supplied.

The results show FUELS to outperform Pseudo-MML at all noise levels, with the discrepancy increasing along with the noise level.

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