1. Introduction

In this paper a literature survey of the differing image enhancing techniques used in digital image processing was carried out. The aim was to discover which techniques are the most efficient, and to determine which technique best applies to the thesis project undertaken, which is visual tagging.

Visual tags are small labels affixed to objects and captured by camera in order to identify them or to provide a link to electronic information associated with these objects. A label’s appearance encodes some value to be read and interpreted through image analysis.

Where the problem occurs is that accurate reading of tags under varying environmental conditions (i.e. changing in light intensities) is difficult, especially in interactive systems where responses must be immediate.

Thus the objective of my section of the project is to enhance the image of the tag captured by a camera. This will essentially make the tag interpreter (the program that will decode the information held by the tag) more efficient and robust, especially in varying environmental conditions.

For the rest of the paper a discussion on the various image enhancing techniques will be presented, after which a comparison of a few of the techniques will be provided, and finally the paper will end with a conclusion.

2. Image Enhancing Techniques

Image Enhancement looks at trying to improve the visibility of one aspect or component of an image, but this is usually at the expense of the rest of the image whose visibility decreases. For most applications (including this visual tagging project) that look for image enhancement this is not really a problem. Most techniques fall under the spatial domain of image processing.

2 The Spatial Domain

The spatial domain simply describes the conventional view of an image, which is that of a 2D array of pixels. Thus enhancement in this domain generally involves manipulation of pixels by means of modifying the original pixels values of an image based on some predefined rules (this is also known as local or point process). Alternatively, pixel values may be combined or compared to other pixels in their immediate neighbourhood in a range of differing methods. In this section the following techniques will be described:

- Contrast manipulation
- Histogram Equalization
- Laplacian
- Genetic Algorithm technique
2.1 Contrast Manipulation
What occurs in most systems is that once an image is captured and held in memory, the individual pixels are then mapped (using some transformation equation) to a table (a look up table) within the system’s hardware. This look up table of pixel values is then sent to the system’s display device, where the image can be viewed. Thus the pixels of the original image that’s stored in memory does not get modified, and contrast manipulation occurs by reassigning the pixel brightness levels for each pixel within the table.

In general we can manipulate, for example the grey scale values for a pixel, in terms of a transfer function which maps the brightness values of the original image in memory to a displayed value that is stored in the look up table. Thus, according to [1], depending on the transfer function employed the look up table can be modified to increase the visibility of one region, or in both dark and bright regions, provided that some other part of the image is sacrificed.

One of the imaging transformations involves a non-linear relationship which has the property of expanding one portion of the greyscale range while compressing another. [1] Says “In analogue display electronics this is known as varying the gamma (the slope of the exposure-density curve)”. Many of the common transfer functions used involve the variation of this variable. These include:

- A logarithmic function or a square root function has the property of compressing the displayed brightness at the bright end of the scale, while expanding those at the dark end.
- An inverse log or squared function will do the opposite of the above
- An inverse function will produce a negative image

2.2 Histogram Equalization
[2] Says “The histogram of an image represents the relative frequency of occurrence of grey levels within an image”. Histogram modeling techniques are used to modify the greyscale range and contrast values of an image such that its intensity histogram fits a desired shape.

Histogram Equalization is used to modify an input image's intensity histogram in order to obtain an output image with a uniformly distributed histogram. The resultant effect will be that the output image will have a perception that overall contrast is optimal (thus the image is enhanced).

The process of histogram equalization involves the use of a transfer function which reassigns the brightness values of display pixels based on the input image histogram. The process does not affect individual pixels brightness order (that is they remain brighter or darker than other pixels) but only modify/shift the brightness values so that an equal number of pixels have each possible brightness value i.e. the process can be represented by the following simplified mathematical equation(found in [1]):

\[ K = \sum_{i=0}^{N} \frac{N_i}{T} \] (1)
What equation (1) says is that for each brightness level, $j$, in the original image the new assigned value $K$ is equal to the sum of the number of pixels in the image with brightness equal to or less than $j$ (i.e. $N_i$) divided by the total number of pixels, $T$.

In more complicated cases, the image histogram may not be a good representation for local statistics in two separate parts of the image. In such a case Histogram Equalization may not enhance the image well enough to represent the two areas. In such a case another algorithm, known as Adaptive histogram equalization, is more appropriate. In this algorithm the image histogram is divided into several rectangular domains, the histogram equalization is then applied to each of these domains. Once this is completed the brightness levels are modified to match across boundaries.

The following figures show the difference between Histogram equalization and Adaptive Histogram Equalization in enhancing images (The figures and comments were obtained from [3]):

Figure 1 shows a standard MRI image with the corresponding gray-scale histogram. The histogram has a peak at minimum intensity consistent with the relatively dark nature of the image.

Figure 2. This shows image after applying histogram equalization (obtained from [3])

Figure 2 above shows the global (entire image) histogram equalization and the final gray-scale histogram. Comparing the results with the figure above we can see that the distribution was shifted towards higher values while the peak at minimum intensity remains.

Figure 3. Image after applying Adaptive Histogram Equalization (obtained from [3])

Adaptive histogram equalization shows better contrast over different parts of the image. The corresponding grey-scale histogram lacks the mid-levels present in the global histogram equalization as a result of setting a high contrast level.
2.3 Laplacian
The Laplacian is an edge enhancing algorithm. It performs local, or neighbourhood equalization of the brightness levels of image pixels. The result is that the output/displayed image shows an increase in local contrast at the boundaries.

Shown below is a simple 3x3 Laplacian operator which is applied to a neighbourhood of pixels (obtained from [1, pg 225]):

\[
\begin{array}{ccc}
-1 & -1 & -1 \\
-1 & +8 & -1 \\
-1 & -1 & -1
\end{array}
\]

This operator is understood to mean that the central pixel brightness value is increased by 8, while the brightness values of all the surrounding pixels are subtracted from the central pixel. A consequence of this is that in regions where the brightness values are uniform this operator sets the brightness values of the neighbouring pixels to zero. But when one of these neighbouring pixels becomes the central pixel, it has the same effect as the previous pixel. Thus all pixels with uniform brightness inadvertently get enhanced by a similar ratio with this procedure. This means that only points, edges or lines benefit from this operation since the brightness levels will be non-uniform within the neighbouring pixels (a large change in brightness level usually indicates the presence of an edge). Hence the overall effect of this operation is that the edges of an image are enhanced.

The output image produced from the application of the Laplacian algorithm is not easily interpretable, but the subtraction of the original image with the laplacian image produces an image which seems sharpened when compared with the original. Figure 4 below shows this characteristic:

![Figure 4. Original image](image1)

![Figure 5. Image after application of laplacian operator](image2)

![Figure 6. Final Enhanced Image after subtraction of figure 4 from figure 5.](image3)

2.4 A Genetic Algorithm Technique
The Genetic Algorithm (GA) technique is essentially a searching strategy that is
modelled around the evolution of a population of individuals. GAs have generally been used to solve difficult optimisation problems in various fields. In terms of image processing, GAs have been used for image compression, reconstruction, segmentation, and enhancement.

[6], discusses image enhancement of grey-scale images with the use of GAs and real coded chromosomes. Real coded GAs differ from the classical approach (which codes chromosomes as a binary string of fixed length) by coding the chromosomes as a set of genes. Each real valued gene then represents a parameter of the optimization problem. According to, [6], this scheme has proved effective since it avoids the negative artefacts that generally plague the binary string version due to the mutation process of the GA.

[6], uses the GA model to partially automate the subjective evaluation of an image by a human interpreter. What this means is that the algorithm will try to automatically identify targets within an image and then enhance those targets. The initial image produced from the process does not usually fit the demand for visual interpretation, thus some manual intervention (for adjusting the contrast levels) is required during the process (hence the reason to call the procedure partially automatic). [6], calls this as modelling the user behaviour.

The GA model used by [6] is as follows:

- The Fitness of each chromosome (which represents an image), is defined as a subjective fitness score between 0-10. It is here where human intervention occurs, since it is a human interpreter that assigns the fitness of each individual chromosome. The interpreter may set the fitness based on the brightness and enhancement of certain areas of an image. The result of this, is that the final output image will be enhanced in a manner that the user desires. This operation would be too human intensive if every chromosome was to be considered, thus the author ([6]), developed a method whereby the human interpreter only looks at a subset (Θ) of the chromosomes from the total population size(N).

The chromosome coding scheme works with the features in an image that the GA has to evolve. This is essentially the brightness levels/intensity of each pixel in a grey scale image. The maximum number of shades of grey (denoted as \(N_g\)) that will be used is a constant that is determined before hand. But the chromosome only codes the intensity values of a small subset of \(N_g\) (denoted \(n_g\), which is equivalent to the length of the chromosome. \(n_g\) is also known as a knot), while the rest \((N_g - n_g)\) is determined through interpolation of a spline curve.

Figure 7 below demonstrates this:
- The selection mechanism uses an elitist approach so that the best chromosome perpetuates through subsequent generations. The remaining chromosomes go through a procedure known as tournament selection. This is a simple mechanism whereby random chromosomes in the mating population are paired together, and the fittest chromosome in the pair is then picked up. This procedure is repeated for a certain number of steps, with the remaining chromosomes mating.

- The crossover operation used gets a better mix of the genetic material from parental chromosomes. Here the author, [6], used the crossover operator known as the Gaussian Uniform Crossover. [6] claims that this operator gives a better mixing of the genes than the classical operator defined by [12], and results in better contrast with evolved images.

- The mutation operator used was uniform mutation, which is also found in [12].

A practical result of using this algorithm is shown in the figure 8 below. Table 1 shows the parameters used, which include $T_{max}$, which is the maximum number of generations the program will run through, $\eta$, which specifies that every $\eta$th image in a population set outside of $\Theta$ be evaluated by the human interpreter.

<table>
<thead>
<tr>
<th>$N$</th>
<th>$T = n_g$</th>
<th>$T_{max}$</th>
<th>Mutation rate</th>
<th>Xover rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>10</td>
<td>20</td>
<td>0.05</td>
<td>0.9</td>
</tr>
</tbody>
</table>

(Table 1 obtained from [6]).

[6], feels that from the experiments they have carried out their GA-based enhanced images are better than the original images, and may have better contrast than the histogram equalization method, that was used for comparison.

### 2.5 Other Techniques

There are many other popular techniques for image enhancement that will not be covered in this paper. Some of these include the Sobel and kirsch operators (found in [1] and [4]), unsharp masking (found in [1], [4], [5]), rank operations (found in [1] and [4]) and texture enhancement (found in [1]).
3. Comparison of Competing Techniques

Table 2 below, summarises the properties of some of the image enhancing techniques discussed.

<table>
<thead>
<tr>
<th>Technique</th>
<th>Property</th>
</tr>
</thead>
<tbody>
<tr>
<td>Histogram Equalization</td>
<td>Adjusts the global contrast of an image, by sharing out the intensity levels of each pixel across the image. Thus entire image is enhanced.</td>
</tr>
<tr>
<td>Adaptive Histogram Equalization</td>
<td>Used for local enhancement of a region within an image. Is an extension of Histogram Equalization.</td>
</tr>
<tr>
<td>Laplacian</td>
<td>Used mostly for edge enhancement</td>
</tr>
<tr>
<td>Genetic Algorithms</td>
<td>Used for local enhancement of an image, with minimal human interaction.</td>
</tr>
</tbody>
</table>

Table 2. Summary of image enhancement techniques

The effectiveness of an image enhancing technique is dependant on the application that it is used on, since differing applications require their images to be enhanced in different manners.

But just to get a feel of how competing methods work for a particular application, the paper written by [2], will be discussed.

[2], compares some of the classical techniques with a technique they developed called multi-scale adaptive histogram equalization (MAHE).

The paper written by [2] is based on the analysis of chest CT images and therefore image clarity is vital for effective diagnosis. [2], provides the following reasons why two of the more popular techniques were not employed for this application:

- In terms of Histogram Equalization (HE), [2], believes that although the technique improves global contrast of an image, there may be certain features/regions within an image that require local enhancement. [2], also feels that the method introduces undesirable artefacts and noise.

- Adaptive Histogram Equalization (AHE), performs the local enhancement that HE does not. But [2] claims that this enhancement is so strong that it has the tendency to amplify noise in flat (uniform contrast levels) regions of an image and create ring artefacts at strong edges.

Another technique which [2], feels can compete with MAHE and solve the problems with AHE and HE, is the contrast limited AHE (CLAHE). The CLAHE is a generalization of the AHE, which reduces undesired noise amplification and reduces boundary artefacts.

What [2], proposes is a contrast enhancement method by AHE in a multi-scale paradigm (i.e. MAHE). Multi scale analysis is a method used to decompose a signal into different spatial-frequency components. By passing these components through specific
decomposition filters, desired features of an image can be separated from noise. Thus selected features within an image can be enhanced by modifying the corresponding components.

In the evaluation of MAHE, what [2] did first was enhance an image with each of the competing methods. After which a random set of people were asked which resulting image was enhanced enough without having an uncomfortable amount of artefacts and noise. These images are shown in figure 9 below. The competing methods were unsharp masking, HE, AHE, and CLAHE.

![Figure 9. Contrast enhancement by traditional methods.](image)

According to [2], the CLAHE enhanced image was uniformly selected by the group of people.

[2], then performed the next step in the evaluation process, which was to compare CLAHE with MAHE. What [2] did was obtain 109 chest CT images from a database and then enhance each of those images using MAHE and CLAHE. Three board certified radiologists, were then used to compare the resulting images. Figure 10 below shows a sample of the images used.
Figure 10. An enlarged display of a chest CT lung region containing detail lung structures and lung nodules, (a) original image, (b) CLAHE enhanced image, (c) MAHE enhanced image. (Obtained from [2]).

According to [2], the radiologists believed that MAHE was superior in detecting air cysts within the images. But CLAHE was superior in detection of small nodules.

[2] explains that CLAHE was found to be increasing the size of the nodules after enhancement. [2], then claims that this is a property which is known to be a recognized limitation of CLAHE. That is it de-emphasizes small regions of sharp contrast change in an image.

MAHE, on the other hand, [2] claims does not change the size of small nodules. This can be seen in figure 10.

In conclusion [2], feels that MAHE shows promising results for chest CT interpretation.

4. Other Applications

Here I briefly list some of the more interesting applications that involve image enhancement:

- [8], describes how image enhancing techniques that are generally used for grey scale images can be extended to apply to colour images. Essentially the colour image is decomposed into background and texture components (using a median filtering algorithm), which are then multiplied by a set of weights. The result of this is an output image whose texture is enhanced.

- [9], describes the use of the unsharp masking algorithm to enhance the perceptual quality of an image containing depth information. They do this by introducing additional depth queues within a complex image. The final result is an image which has its contrast, colour and other parameters enhanced. This procedure can be applied to variety of complex images such as complex landscape data and technical artefacts.

- [10], describes an image processing technique that is used to enhance text image that is captured by a hand held camera. The significance of this technique is its speed and robustness under poor lighting and focus conditions.

- [11], works with the idea that image comprehension for a viewer is
improved when visual cues are added to the gaze path of semantically important areas. With this theme, [11], proposes a computational model that attempts to simulate feature specific neuronal responses to an input image that has been filtered with a center surround filter. The process produced encouraging results, but the author feels that the procedure still needs to be refined.

5. Conclusion

Having reviewed the different image enhancing techniques it is difficult to pinpoint which method would be best suited for my application, as the efficiency of each method is mostly application based. The classical approaches (e.g. histogram equalization) may be sufficient since the TAG images to be enhanced are simple compared to the other more complex images described in this paper.

Another factor, which is especially important for the visual tag project, is the speed at which these algorithms operate at. This was rarely discussed in the papers reviewed, but can easily be resolved through practical implementation.

Thus the determination of the most appropriate technique will have to be done by experimenting with several of the techniques described here.

6. References


Proceedings of the 30th annual Southeast regional conference.


