Novel Classifier for a Smart Traffic Network

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Thomas Courtney

3175353

Supervised by Assoc. Prof. Kaushik Mahata

School of Engineering

University of Newcastle

I hereby declare that this dissertation is all my own work, except as indicated in the text:

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Date _____ / _____ / _____

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Chapter 1

Introduction

Economies of the world have been industrializing for over two centuries [1] and the consequent advent of machines and factories has seen a great migration of humanity from farmlands to cities. Such a shift in population density has posed a plethora of infrastructural challenges and led to many iconic solutions to high density living, like the skyscraper, subway train and traffic light. One unfortaunte metropolitan trait, however, continues unabated and is in fact growing in size [2] - it is traffic congestion.

Road transport contributes 16.5% of global CO2 emissions [3] and costs the US $305 billion of productivity per year alone [4][5] thus even a small improvement in traffic efficiency will yield great benefit to society and the future of the planet. Unfortunately its persistence is only an indicator of its difficulty to solve.

There is no single solution to the problem of traffic congestion, whether it be the building of tunnels, the conversion of traffic lights to roundabouts or the widening of roads though several studies [6][7][8][9] have found that the integration of several lightweight and inexpensive techniques is a far more efficient and effective approach than the aforementioned heavyhanded methods. A 'Smart City' is such an approach, and part of its design is to deploy many devices in an urban area that collect data [10] which is then transmitted and processed to make useful conclusions about a system. This technology could be applied

to collect traffic data more completely and inexpensively than is currently the case. Data of interest includes traffic volume and vehicle speed.

Current widely employed methods of traffic data collection [11] have inherit weaknesses that justify a movement to new techniques that exploit advantages provided by the latest technology. For example, manual counting that requires a person be visually counting traffic is very expensive hence is can be used for short surveys limiting the completeness of the data collected and necessitating extrapolation at a cost to accuracy. Automatic methods of data collection such as inductive loops and piezo-electric sensors are able to measure speed and mass of vehicles due to the change in electric field that generate as they pass a sensor however these systems are embedded in roadways and thus have high installation and maintanence costs. Less invasive automatic methods of data collection include pneumatic road tubes that sense change in air pressure as a tire passes over them. These systems are often temporary and accuracy is subject to temperature and traffic conditions. Infra-red sensors are inexpensive but cannot provide coverage across multi-lane roads and magnetic sensors embdedded in roadways often cannot differentiate between closely placed traffic.

A single *modular* lightweight system capable of performing all the functions of the aforementioned devices would be advantaged by significantly lower maintenance fees, dyanmic installation capabilities and efficiency borne of the simplicity of relying on a single system set. Further, if many system modules were employed at key locations and data was trasnmitted in realtime to a central database for processing a complete picture of the state of the traffic system at anytime could be developed. A module running a computer vision algorithm with a small camera module would be able to complete such functions.

Computer vision is a versatile method by which image classification and object tracking may be achieved. An algorithm can be tailored to produce high accuracy real-time results requiring only images as input. Computer vision attempts mimic human vision's ability to rapidly identify objects like separating a vehicle from its surroundings and tracking its

movement. An increasingly effective method of image classification utilizes machine learning and trains a neural network to recognise objects in an image, however, this method is hindered by the large amounts of computational power required to train the network and the many thousands of data samples to train the network on. In a specific use-case like traffic monitoring a specialized algorithm that does not depend on a neural network but image processing techniques alone can yield high quality results. The implementation of a robust computer vision algorithm for traffic monitoring is not trivial however, and many techniques may have to be choreographed for the algorithm to behave as intended.

It is the objective of this report to explain the design and operation of a lightweight and discrete traffic data collection module whose capabilities to estimate traffic speed and volume depend on an underlying computer vision algorithm. Further the module will trasnmit real-time results to a central database. It's basic structure is comprised of a Raspberry Pi microcontroller mounted above a road of interest that collects data about the traffic conditions of that road and transmits that data and a video feed of the road across a network to a central database. The overall system can be scaled to include many microcontroller nodes transmitting information.

Chapter 2 explores the relevant theoretical background undpinning the computer vision techniques implemented by the algorithm. This begins with the fundamental qualities of a digital image and ends with an explaination of the probabilistic model that is used to determine what is a car and what is not in the algorithm.

Chapter 3 details the system's overall design and how its susbsytems interface with each other to produce a functional data collection product. Subsystems include the Computer Vision, Networking, Hardware, Data Storage and Organization and The User Interface. The Computer Vision section in particular explains how the theoretical principles discussed in Chapter 2 are employed.

Chapter 4 outlines the capabilities of the system and the results it is able to produce whose analysis helps identify the strengths and weaknesses of the system.

Chapter 5 summarises how well the system satisfied the requirements it was designed to meet and also suggests augmentations that could be made to the system to imrprove its performance and applicability.

Chapter 2

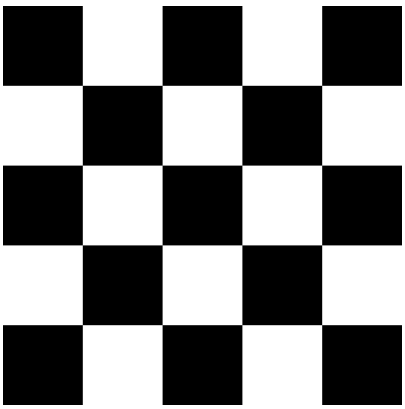
Theoretical Background

This section of the report expands upon the theory behind the design of the system. Digital image processing and computer vision are broad fields and so only concepts relevant to the system are explored.

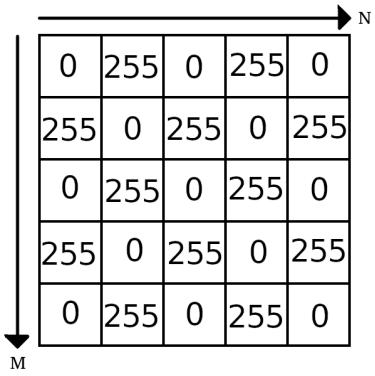
2.1 Digital Images

Digital images consist of discrete valued data points called pixels arranged in a grid where it is the value of these pixels that determine the colour of each cell. A pixel's value is also called its *intensity* and lies within a range of values determined by the image's encoding. For example an 8-bit image has pixel values in the range $[0, 255]$.

Digital images are often represented as a 2D array of values where each cell corresponds to an intesnity. In software in particular, digital images are stored and manipulated as arrays. An image's array is $M \times N$ pixels in size, which is also its resolution. Notice that in Figure 2.1 the lowest value is 0 (black) and the highest value is 255 (white). All other colors that can be represented by 8-bits are between these two values.



(a)



(b)

Figure 2.1: (a) A Simple 8-bit Image (b) Array Representation of Image.

2D array representation allows pixels to be referenced by their relative position in the M and N directions. Furthermore, M and N may be substituted for the x and y axes of the Cartesian plane. In fact, a digital image is just a two dimensional function where each pixel is described by a coordinate (x,y) and an intensity (z) at that point.

$$z = f(x, y) \tag{2.1}$$

This representation is extremely useful as it means that two dimnesional operations may be applied to a images. Rates of change, derivatives, of a digital images are important in computer vision because they help to identify features like lines and object edges. Figure 2.2 is a 3D plot of a 2D image where you can see that there is a rapid change in value between different coloured squares, shown as steep cliff edges.

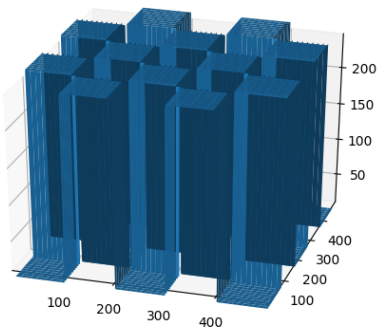


Figure 2.2: Surface Plot of Figure 2.1a

2.2 Linear Filtering

Filtering an image is a way to augment or extract information from it. Linear filtering is a mathematical operation on a neighbourhood of pixels in an image that outputs a weighted average of the pixels in that neighbourhood. It is the weightings of a filter, known as filter coefficients, that determine the effect of the filter. These weights are stored in a matrix called a mask or kernel (see Figure 2.3) that's then convolved with an image (see sections 2.2.1 & 2.2.2).

$$Kernel = \frac{1}{\sum_{i=0}^{M}\sum_{j=0}^{N} c_{i,j}} \begin{bmatrix} c_{0,0} & c_{0,1} & \dots & c_{0,n} \\ c_{1,0} & c_{1,1} & \dots & c_{1,n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{m,0} & c_{m,1} & \dots & c_{m,n} \end{bmatrix}$$

Figure 2.3: General Form of a Linear Filter

2.2.1 Correlation

The application of a linear filter $h(u, v)$ to an image $f(i, j)$ may be described as follows

$$g(i,j) = \sum_{u=-k}^{k}\sum_{v=-l}^{l} f(i+u, j+v)h(u,v) \tag{2.2}$$

$g(i, j)$ is the output image. Performing correlation with a filter may be notated more concisely by the correlation operator.

$$g = f \otimes h$$

Correlation measures the *similarity* between two signals and as both digital images and linear filters are two dimensional signals by correlating them we can see where they are most similar. Performing correlation between them will produce an output image whose

highest values correspond to where the image and filter were most similar [12]. This is an important operation in image classification as it can be used to highlight features in an image and diminish everything else by correlating a filter that describes the desired feature. The feature could be as simple as a straight line as in a Sobel filter (Figure 2.4) or as specific as the outline of a car wheel. This method of feature detection is called *templating*.

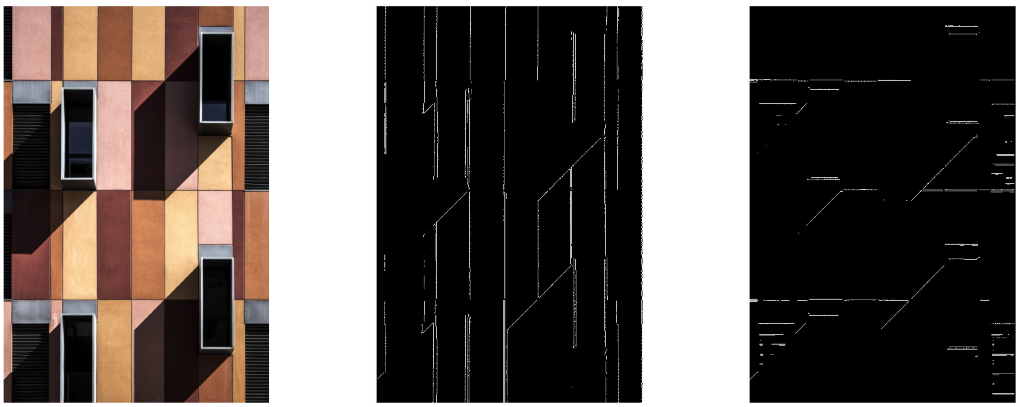
In Figure 2.5 vertical and horizontal Sobel filters are applied to produce images that emphasise lines that match the orientation in the respective filter, the lines that are most similar. The result is black and white as the initial output image's intensities have been thresholded to either be 1 or 0. I.e. where initial output image is $F(x, y) = z$ and T is the threshold intensity:

$$BinaryOutput = \begin{cases} 1 & \text{if } z >= T \\ 0 & \text{if } z < T \end{cases} \tag{2.3}$$

$$\begin{bmatrix} -1 & -1 & -1 \\ 2 & 2 & 2 \\ -1 & -1 & -1 \end{bmatrix} \qquad \begin{bmatrix} -1 & 2 & -1 \\ -1 & 2 & -1 \\ -1 & 2 & -1 \end{bmatrix}$$

(a) Horizontal Sobel Filter Mask (b) Vertical Sobel Filter Mask

Figure 2.4: Sobel Filters



(a) Image by Simone Hutsch (b) Vertical Sobel Filter (c) Horizontal Sobel Filter

Figure 2.5: Application of Sobel filters to exagerate lines.

Correlation is *shift invariant*, which means that it does the same thing no matter where in an image it is applied. To satisfy this property correlation may be superpositioned

$$a(f_1 + f_2) = af_1 + af_2$$

and abides by the shift invariance principle

$$g(i,j) = f(i+k, j+l) \Leftrightarrow \ (h \circ g)(i,j) = (h \circ f)(i+k, j+l)$$

Correlation has the side effect of flipping both horizontally and vertically the location of output points relative to the center point (*reference point*) in the original image which may be undesirable as can be observed in Figure 2.6.

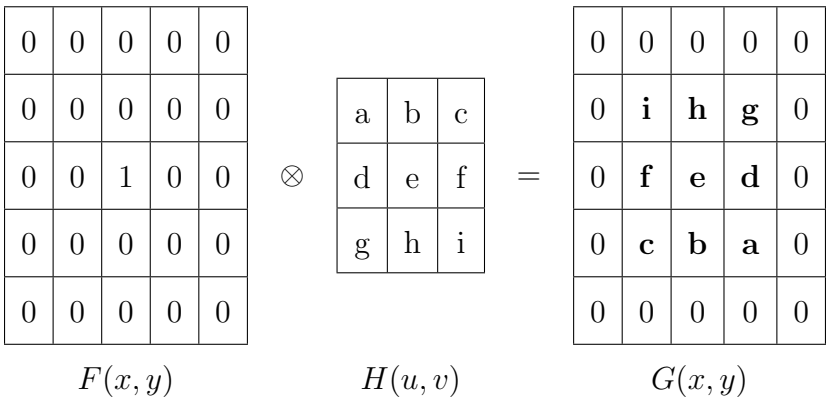


Figure 2.6: Correlation of a filter and an image.

2.2.2 Convolution

Convolution is also a linear operation that is shift invariant. It is very similar to correlation except that where correlation measure similarity between signals convolution measures the effect of one signal on another. It is described mathematically by the expression,

$$g(i,j) = \sum_{u=-k}^{k} \sum_{v=-l}^{l} f(u,v)h(i-u, j-v)$$

Notice that the filter $h(i,j)$ is rotated 180 degrees. This causes the output's orientation to match the original image. Convolution may be notated as follows,

$$g = f * h$$

Convolution is essentially the same as correlation except that it doesn't flip the output relative to the original image as can be seen in Figure 2.7 and it is the operation that is performed when a linear filter is applied to a digital image.

0	0	0	0	0
0	0	0	0	0
0	0	1	0	0
0	0	0	0	0
0	0	0	0	0

$F(x, y)$

$*$

a	b	c
d	e	f
g	h	i

$H(u, v)$

$=$

0	0	0	0	0
0	**a**	**b**	**c**	0
0	**d**	**e**	**f**	0
0	**g**	**h**	**i**	0
0	0	0	0	0

$G(x, y)$

Figure 2.7: Convolution of a filter and an image.

2.2.3 Kernels

Kernels are just the weightings that define the characteristics of a filter, also known as a filter's mask. A filter kernel is nearly always square so as to have a center cell which sits atop a reference pixel. The result of the filter's application at that reference pixel will be stored in the output image at the location of the reference pixel. Notice in Figure 2.8 how the mask sits over the reference pixel.

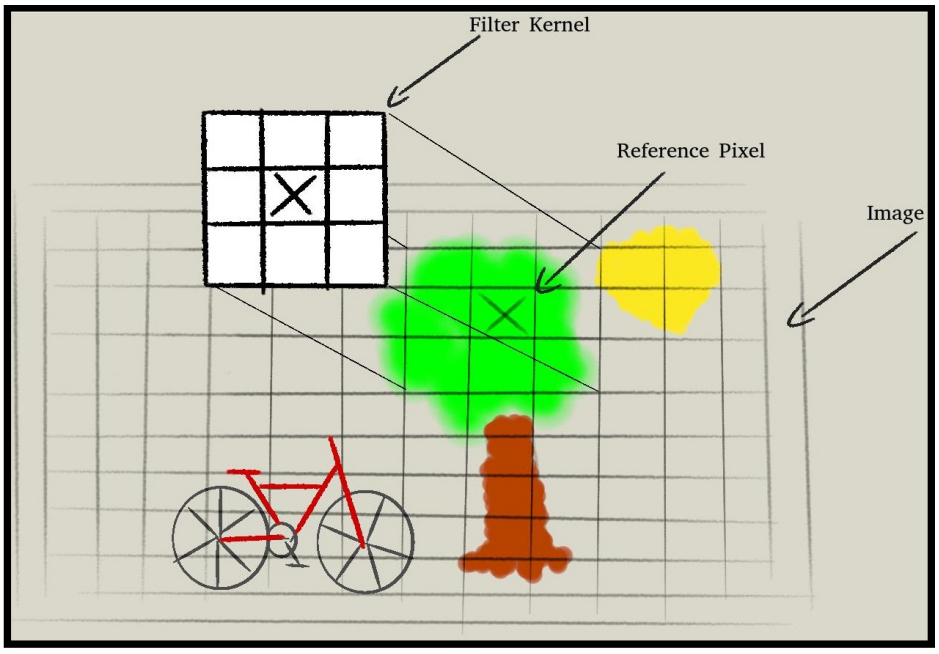
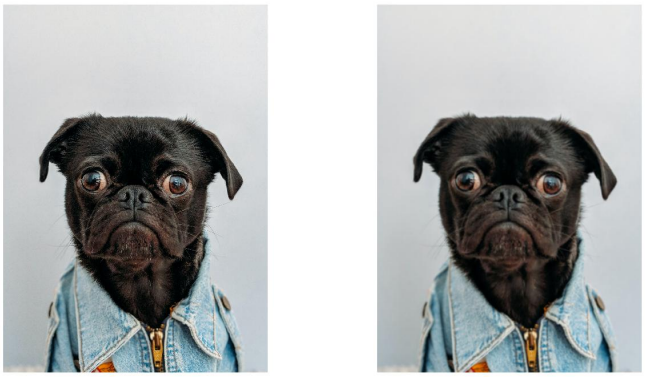


Figure 2.8: Visualization of a Filter Kernel Application

Box Filter

A box filter also known as a moving average filter simply outputs the average of its inputs because the filter weights are evenly distributed (Figure 2.10). By passing this filter over an image its sharpness is reduced because the filter flattens out difference in values generating a smooth effect which can be observed in Figure 2.9. This filter's 'flattening' effect is useful for removing noise which stands out from other pixel values.



(a) Img: Charles Deluvio (b) Blurred pug

Figure 2.9: Application of a 17x17 Box filter to blur image.

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Figure 2.10: 3x3 Box Filter Kernel

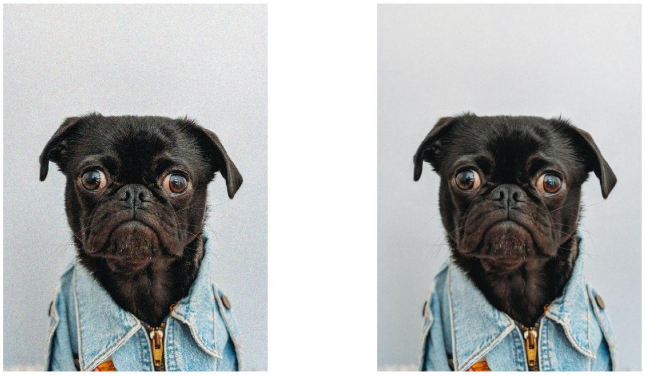
Gaussian Kernel

The Gaussian is a significant kernel in image processing as it is good at filtering out noise. This kernel models the Gaussian function (see Section 2.5) or normal distribution. It works in a similar fashion to the moving average filter but is superior at filtering noise as it addresses two properties about images that are generally true,

1. The 'real' value of a pixel is probably the same or similar to its neighbors.

2. Each pixel of noise in an image is added independently.

The Gaussian addresses both of these qualities by having high value cooefficients at the filter's center and lower values tapering out to the edges of the filter (Figure 2.12). This means that values closer together are more strongly correlated than those further away from the reference pixel as can be observed in the 7x7 Gaussian filter kernel in Figure 2.11.



(a) Noisey pug (b) Denoised pug

Figure 2.11: Application of a 7x7 Gaussian filter to denoise image.

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.0002 & 0 & 0 & 0 \\ 0 & 0 & 0.0113 & 0.0837 & 0.0113 & 0 & 0 \\ 0 & 0.0002 & 0.0837 & 0.6187 & 0.0837 & 0.0002 & 0 \\ 0 & 0 & 0.0113 & 0.0837 & 0.0113 & 0 & 0 \\ 0 & 0 & 0 & 0.0002 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

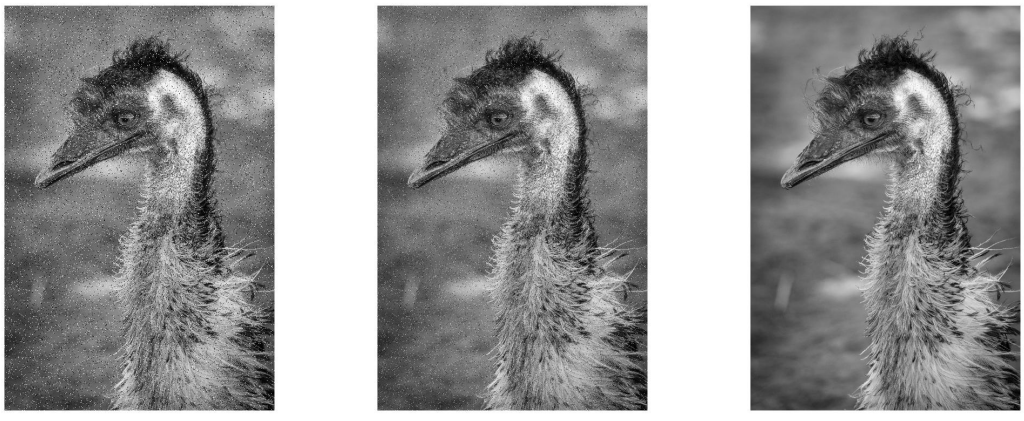
Figure 2.12: 7x7 Gaussian Filter Kernel, Sigma = 0.5

2.3 Non-Linear Filters

Non-linear filtering is set of operations that is performed on a neighbourhood of pixels in a digital image. In linear filtering the sum of an image's responses to two or more filters is the same as the sum of those filters applied to the image once. This is not the case in non-linear filtering, however there are scenarios where a non-linear filter can achieve superior results. A non-linear filter's application to an image is not simply it's convolution with that image.

2.3.1 The Median Filter

The median filter is useful for denoising an image, much like the linear box and Gaussian filters (section 2.2.3). A median filter's applications returns the median valued pixel found in the neighbourhood under its mask. This is a more complex operation than to convolve one signal with another however it can be computed in linear time [13]. It is superior to the Gaussian filter at denoising images, particularly where intensities vary largely, which would skew the weighted average of a linear filter. In Figure 2.13 the median filter demonstrates a superior ability to remove salt and pepper noise as compared to the Gaussian filter.



(a) Salt and Pepper Noise (b) 7x7 Gaussian (c) 7x7 Median Filter

Figure 2.13: Filtering out salt and pepper noise with Gaussian and median filter. Original image by Grant Durr.

2.4 Morphology

Morphological operations are yet another set of neighborhood operators however unlike filtering they are designed to modify the shape of objects in binary images specifically. Producing a binary image from a coloured one involves first converting that image to grayscale and then thresholding (Equation 2.3) its intensity such that pixels are converted to a 1 or 0 depending on whether they lay above or below the threshold (Figure 2.14). These are useful operations when you wish to modify an object's shape in order for it to fit some criteria, for example its total area or whether or not it's an open or closed contour. All morphological operators work by convolving a binary *structuring element* with an image and thresholding the output pixel. There are two fundamental morphological operations, *dilation* and *erosion*, that comprise all others.

(a) RGB Image (b) Grayscale Conversion (c) Binary Thresholding

Figure 2.14: Conversion of an RGB image to a binary image. Original image by Adam Birkett

Dilation

Dilation fills out or enlarges an object in a binary image in a way that is characterised by the specific structuring element used for the operation. A structuring element itself is just a binary image, generally a lot smaller than the target image itself, of a similar nature to a filter kernel, having an origin or reference pixel at thei center. In Figure 2.15b the

dilation causes objects to fill in gaps and even small spurious objects are inflated. This is because the structuring element 2.15f is simply a 9x9 pixel square where each convolution of the filter with the image outputs a 1 if the element overlaps at least one pixel of a binary object. This is a useful operation for filling in gaps in objects or thickening lines.

Erosion

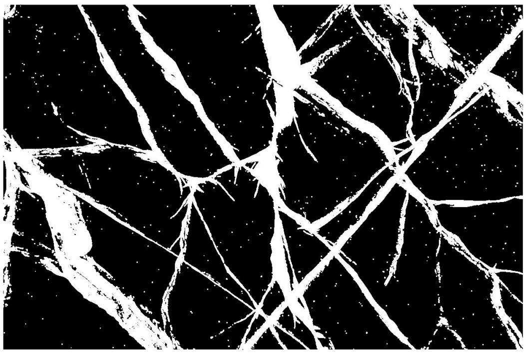
Erosion performs the opposite function to dilation causing objects to contract rather than grow. Again, the structuring element is convolved with a binary image but and the output is placed at the structuring element's origin in the resulting image. Intuitively, wherever the structuring element is not completely inside an object the output is stored as black. In Figure 2.15 the structuring element we see that many smaller entities are erased from the image and many salient features are removed from large objects. This has the effect of 'cleaning up' the binary image of all speckle and spiky features, the nature of the cleanup depends on the size and shape of the structuring element, in this case the structuring element (2.15f) is a simply square of size 9, so it acts like an eraser wiping anything that's approximately the same size or smaller.

Opening and Closing

Opening and closing are composite operations comprised of an erosion and dilation, each of which may use the same or different structuring element. An opening is an erosion followed by a dilation which is usel for isolating and cleaning up objects that might be just 'kissing' by first removing entities that are probably too small to be of interest, refining of object edges and breaking of thin connections and then smoothing of the remaining objects. In Figure 2.15d it can be seen that many spiky entities are removed and some thin connection broken creating discrete objects that are smooth in somewhat thicker. Closing is the opposite ordere operation to opening performing first a dilation then an erosion. This is useful is you want to join objects together and preserve objects that

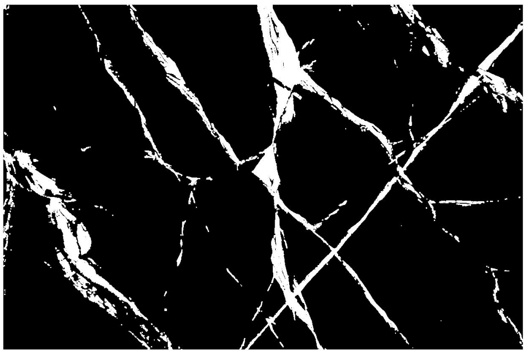
might have been wiped out by an initial erosion. In Figure 2.15e it can be seen to close many small gaps between objects and fill them in but still result in smooth large objects as a consequence of the erosion. Therefore, an opening can be thought of as useful for separating objects from one another and closing is good at joining them together.

(a) Binarized image



(b) Dilation

(c) Erosion



(d) Opening

(e) Closing

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

(f) Structuring element

Figure 2.15: Effect of morphological operations on a binary image using a 9x9 square structuring element. Original image by

2.5 The Gaussian

The Gaussian provides a consistent model for normal distributions, aka the bell curve, as in Figure 2.16 & 2.17. Normal distributions follow the *central limit theorem* where in if a histogram is taken of a sufficiently large number of independent random variables they will distribute with a central most probable value and symmetrically fall away either side of this value. Many datasets follow this trend closely enough that the Gaussian can be used to approximate a probability distribution for them.

The Gaussian function is defined by three parameters, its mean μ, standard deviation σ and amplitude A.

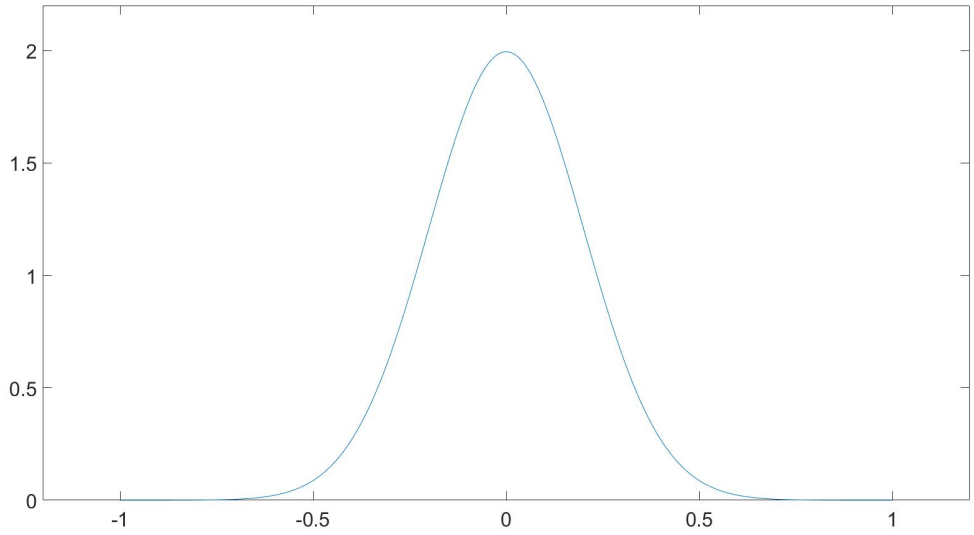


Figure 2.16: The Gaussian Function in 2D with μ=0, σ=0.2 and $A = 2$.

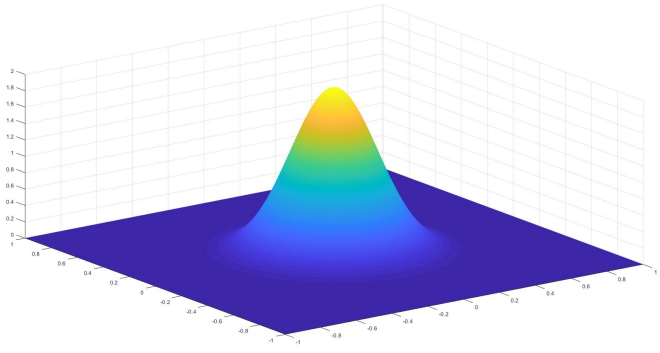


Figure 2.17: The Gaussian Function in 1D with μ=0, σ=0.2 and $A = 2$.

The general one dimensional Gaussian is described:

$$f(x) = \frac{A}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} \tag{2.4}$$

The mean value, the central limit, of the sample distribution is the value that has the greatest likelihood[1] in the distribution. The standard deviation is how much the distribution is spread out, the greater the standard deviation the fatter the distribution. The amplitude is the likelihood at the mean of the distribution. In Figure 2.16, for example, the likelihood of a value being 0 is 2. Generally, the curve is used to determine a sample's probability density within a value range. This is the area under the distribution given an interval and is calculated using integration, as shown in 2.5.

$$P(x) = \int_a^b \frac{A}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} dx \tag{2.5}$$

Data sets can have many dimensions and distributions need to be able to express all of them. The notation for a multi-variate Gaussian distribution, for a k-dimensional random vector $\boldsymbol{X} = (X_1, \ldots, X_k)^T$, is

[1]Likelihood is the value of the distribution given a fixed sample. Probability is the value of a sample given a fixed distribution.

$$\boldsymbol{X} \sim \mathcal{N}_k(\mu, \sigma^2) \tag{2.6}$$

2.6 Clustering

Clustering is a method of segmenting an image into disjoint sets known as classes. This is useful for separating types of features or objects in an image. For example in Figure 2.18 the toy car has been segmented from the background.

(a) Image by Gustavo, Upsplash.

(b) Segmentation of car from background.

Figure 2.18: Segmentation of toy cars using K-Means Clustering.

In an image every pixel can be individually classified or groups of pixels known as super-pixels may be treated as single entities. Entities are sorted based on their similarity. For example, a pixel's intensity is a feature that could be used to cluster it with other pixels of similar intensity. As seen in (2.7) an entity's comparable traits may be represented by a feature vector. An entity may have any number of features which as also regarded as dimensions, d.

$$\vec{v} = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{bmatrix} \tag{2.7}$$

2.6.1 K-Means

There are many methods by which to cluster, K-Means is a popular method due to its speed and simplicity. Data points are sorted into one of K clusters where the average value of the cluster is stored in a central data point known as the cluster centroid. Centroids may initially be randomly generated or selected from the given data set.

Data points or samples are placed in the class of the centroid that is closest to them. The distance between them is the Euclidean Distance between their feature vectors as in 2.8.

$$D(\vec{p}, \vec{q}) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \ldots + (p_n - q_n)^2} \tag{2.8}$$

K-Mean's algorithm proceeds as follows:

1. Place the initial K centroids.
2. Assign all data points to their nearest centroid.
3. Update the centroids' values to be the mean of all data points in their cluster.
4. Repeat steps 2 and 3 until a criteria is met, for example until cluster centroids no longer move (converge).

K-means benefits greatly from its low computational cost such that it is oten performed a number of times with different initial centroids and the instance best result is used. The best result is defined as having the smallest intracluster variance. K-Means is disadvantaged by the implicit trait that it formulates clusters of similar sizes. This happens because the algorithm seeks to minimize variance (spread) in each cluster hence the 'ideal' centroid placement will form distributions spherically about centroids. This method cannot disentangle overlapping samples that belong in different classes. In Figure 2.19 clear edges between clusters and sphereical distributions can be observed. The algorithm can only implement *hard assignments*, as opposed to a *soft assignment* that consider the

probability of a sample's class membership.

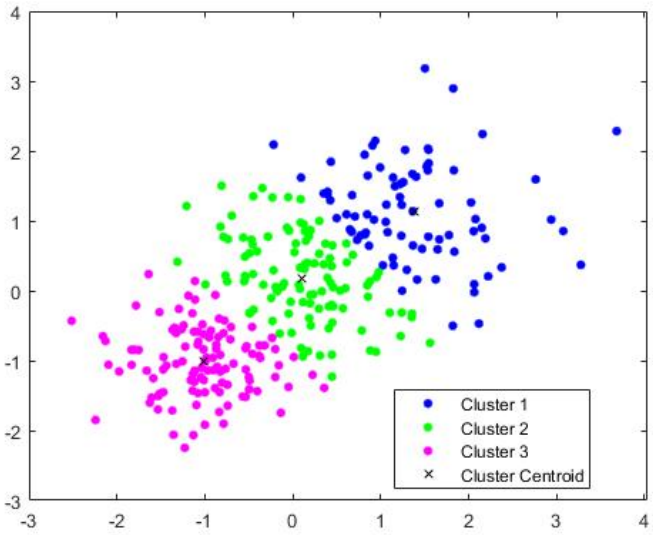
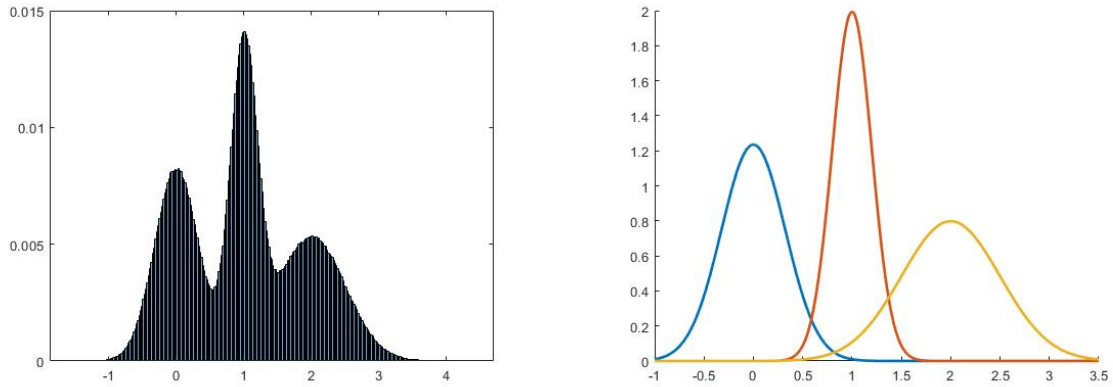


Figure 2.19: K-Means clustering performed on random data.

2.6.2 Mixtures of Gaussians

Mixtures of Gaussian or the Gaussian Mixture Model (GMM) is a method of clustering data that's able to disentangle ambiguous samples by considering a sample's probability of belonging to a class, known as a soft assignment.

Initially, K Gaussian functions are randomly generated corresponding to K clusters. If a dataset has low dimensionality, by taking a histogram of its values the Gasussians' initial conditions can be approximated, as in Figure 2.20a. By superpositioning all of the Gaussians a sample's complete probabilistic model is created, i.e. a model for *all* clusters, see Figure 2.20b.



(a) Normalized Histogram of 1D samples. (b) Gaussians derived from 1D histogram.

Figure 2.20: Formulation of Mixture of Gaussians.

With each iteration of the GMM algorithm the parameters of the model's component Gaussians are tuned according to the covariance between samples in each cluster. In 2.9 X and Y are the variables being compared, $\overline{X}$ and $\overline{Y}$ are variable means and n is the number of samples. For a multidimensional dataset a covariance matrix $\boldsymbol{\Sigma_k}$ will be generated and each Gaussian will require a mean vector $\boldsymbol{\mu_k}$ as opposed to a scalar.

$$Cov(X,Y) = \frac{\Sigma(X_i - \overline{X})(Y_j - \overline{Y})}{n} \tag{2.9}$$

The algorithm seeks the highest covariance possible in each of its clusters. It is by considering the covariance of samples that the GMM is able to best classify ambiguous samples. The higher the covariance (aka correlation) between sample dimensions the more likely it is they belong in the same cluster. This can observed in Figure 2.21, the data being clustered is the same as in Figure 2.19 but notice the elliptical shape of the Gaussian cluster distributions as opposed to the spherical shape of K-Means clustering.

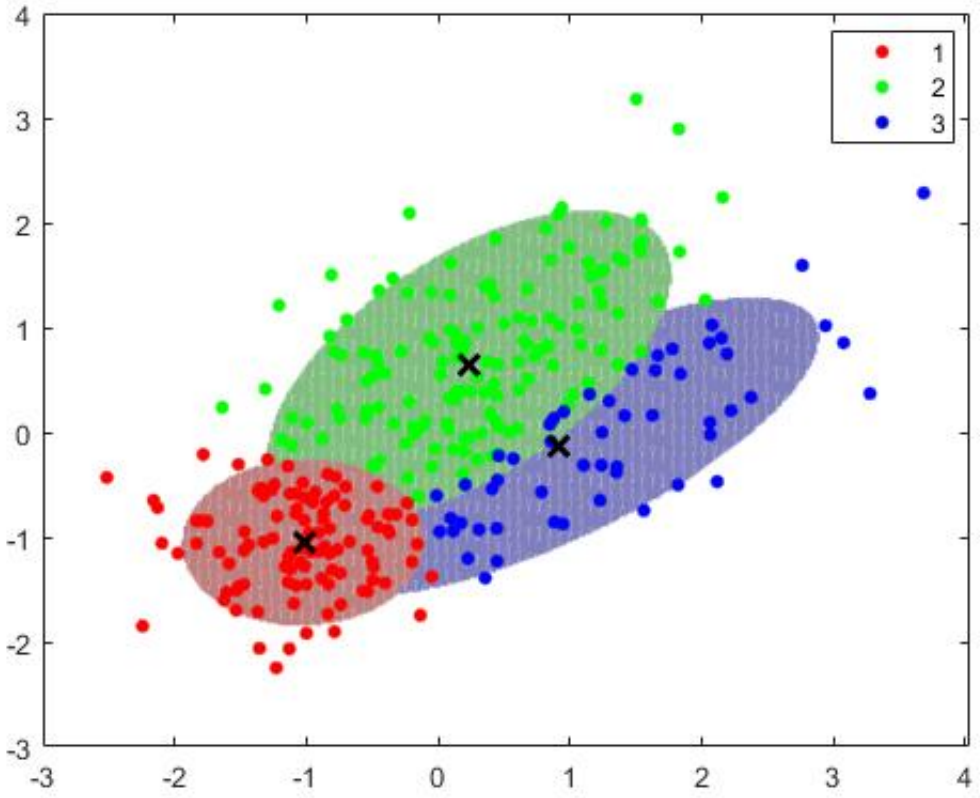


Figure 2.21: Clustering using GMM. X marks cluster mean.

In Figure 2.22 the Gaussians from Figure 2.20b have been scaled to have the amplitudes $\pi_1 = 0.3$, $\pi_1 = 0.5$ and $\pi_1 = 0.2$. These are weightings that give the mixing ratio of the GMM and represent each cluster's proportion of the total samples. The more samples a cluster contains the more likely it is a sample belongs to it. The sum of ratios must add to one because the probability a sample belongs to at least one cluster is one, as defined in 2.10 and 2.11.

$$0 \leq \pi_k \leq 1 \tag{2.10}$$

$$\sum_{k=1}^{K} \pi_k = 1 \tag{2.11}$$

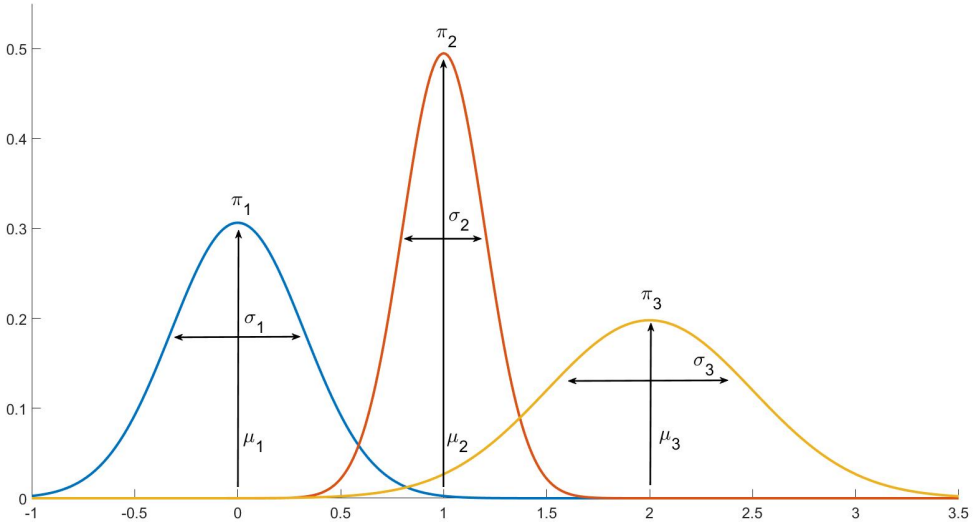


Figure 2.22: Individual Gaussians with scaled weightings.

Each Gaussian's three parameters, mean $\boldsymbol{\mu}_k$, ampltidue π_k and covariance $\boldsymbol{\Sigma}_k$ are updated following each iteration of the algorithm according to the 'Expectation Maximization' algorithm.

Expectation Maximization

Expectation Maximization (EM) is a method of updating the parameters of cluster Gaussians that seeks to maximize a sample's likelihood of belonging to said Gaussians (2.12).

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \tag{2.12}$$

A binary indicator z_i exists for every sample x_i, it is 1 if the sample belongs in the cluster k and 0 otherwise such that $z_{ik} \in \{0, 1\}$ and $\sum_k z_{ik} = 1$. If the data is multidimensional then the sample and inidicator are both vectors, $\boldsymbol{x}$ and $\boldsymbol{z}$. The marginal probability $p(\boldsymbol{z}_k = 1)$ is the probability that a sample $\boldsymbol{x}$ is in cluster k. This quantity is completely specified by the mixture weight π_k for each Gaussian because the area under a Gaussian

component is equal to its mixing ratio, i.e.

$$p(\boldsymbol{z}_k = 1) = \pi_k \tag{2.13}$$

If we know that a sample $\boldsymbol{x}$ is from cluster k the *likelihood* of seeing it in the associated Gaussian is the value of the Gaussian at that point,

$$p(\boldsymbol{x} \mid \boldsymbol{z}_k = 1) = \mathcal{N}(\boldsymbol{x} \mid \boldsymbol{\mu_k}, \boldsymbol{\Sigma_k}) \tag{2.14}$$

The conditional probability of $\boldsymbol{z}_{ik}$ given the value of sample, $\boldsymbol{x}_i$ is denoted as $\gamma(\boldsymbol{z}_{ik})$. This is the probability that a sample belongs to cluster k given its value $\boldsymbol{x}_i$ and is the quantity of interest when trying to classify a sample. Using Bayes Theorem [REF APPENDIX] quantity can be found

$$\gamma(\boldsymbol{z}_{ik}) \equiv p(\boldsymbol{z}_{ik} = 1|\boldsymbol{x}_i) = \frac{p(\boldsymbol{z}_{ik} = 1)p(\boldsymbol{x}_i \mid \boldsymbol{z}_{ik} = 1)}{\sum_{j=1}^{K} p(\boldsymbol{z}_{jk} = 1)p(\boldsymbol{x}_j \mid \boldsymbol{z}_{jk} = 1)} \tag{2.15}$$

$$= \frac{\pi_k \mathcal{N}(\boldsymbol{x} \mid \boldsymbol{\mu_k}, \boldsymbol{\Sigma_k})}{\sum_{j=1}^{K} \pi_k \mathcal{N}(\boldsymbol{x} \mid \boldsymbol{\mu_k}, \boldsymbol{\Sigma_k})} \tag{2.16}$$

To maximize the likelihood of each sample being in each Gaussian the distribution parameters are modified. This is achieved by taking derivatives of the log of the likelihood function (2.12) with respect to each Gaussian parameter and setting the result to 0 to find local maxima. To take the log of the likelihood function assume all samples in are in an $N \times D$ matrix $\boldsymbol{X}$ and the corresponding indicators are in an $N \times K$ matrix $\boldsymbol{Z}$.

$$ln\, p(X|\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \sum_{n=1}^{N} ln\left\{ \sum_{k=1}^{K} \pi_k(N)(\boldsymbol{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \right\} \tag{2.17}$$

The EM algorithm is comprised of [X] steps

1. Generate the initial K Gaussian parameters mean $\boldsymbol{\mu}_k$, covariance $\boldsymbol{\Sigma}_k$ and mixing ratios π_k either randomly or informed by a histogram.

2. Estimate the likelihood sample n was generated by cluster k for all samples.

$$\gamma(\boldsymbol{z}_{ik}) = \frac{\pi_k \mathcal{N}(\boldsymbol{x} \mid \boldsymbol{\mu_k}, \boldsymbol{\Sigma_k})}{\sum_{j=1}^{K} \pi_k \mathcal{N}(\boldsymbol{x} \mid \boldsymbol{\mu_k}, \boldsymbol{\Sigma_k})} \tag{2.18}$$

3. Maximize the Gaussian parameter using derivatives of log likelihood for each parameter.

$$\boldsymbol{\mu}_k^{new} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk}) \boldsymbol{x}_n \tag{2.19}$$

$$\boldsymbol{\Sigma}_k^{new} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk})(\boldsymbol{x}_n - \boldsymbol{\mu}_k^{new})(\boldsymbol{x}_n - \boldsymbol{\mu}_k^{new})^T \tag{2.20}$$

$$\pi_k = \frac{N_k}{N} \tag{2.21}$$

where

$$N_k = \sum_i z_{ik}$$

4. Repeat steps 2 and 3 until convergence of log likelihood (2.12) or parameters.

The Gaussian Mixture Model method of clustering is computationally complex compared to K-Means however it's ability to differentiate ambiguous samples by considering covariance is superior.

Chapter 3

Design

This section of the report details the components that comprise the whole traffic monitoring system and justifies the design choices made and the design principles that were followed.

System Overview

The purpose of this system is to collect the speed and vehicle volume of a road/s continuously. This is achieved by mounting a microcomputer, which will henceforth be referred to as a *node*, on a pole at the location and directing a camera connected to the microcomputer, at the road. The road may be multi-lane travelling in both directions, the system can collect data for all vehicles observed. Speed and volume are sent every 30 seconds to another computer on the same network in real-time. The data is stored in a database and served up to an end user who can query the database for specific node's location and time period. The node converts the images collected by the camera into statistics by running a computer vision algorithm designed to recognize vehicles. This section of the report details the subsystems that comprise the overall system, how they interact with each other and how they were implemented. In Figure 3.1 the overall design flow of the system can be observed.

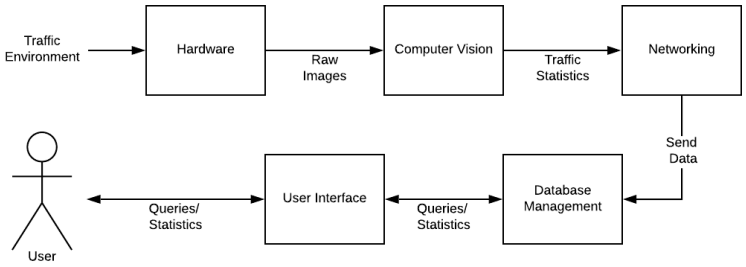


Figure 3.1: Overall System Design

3.1 Computer Vision

The computer vision subsystem is a software component that is designed to recognise and track vehicles in images in order to count them and estimate their speed, henceforth to be referred to as the *detection* component of the system. Each time an image is processed by the detection algorithm several subprocesses are performed in order to manipulate the original image into a state where vehicles have been isolated. These subprocesses can be seen in Figure 3.2. The vehicle tracking subprocess was largely influenced by the work of Adrian Rosebrock [14][15] of PyImageSearch and the vehicle segmentation subprocess was influenced by the work of Andrey Nikishaev [16]. Much of the functionality of the detection system is provided by the Python open source computer vision library, OpenCV [17].

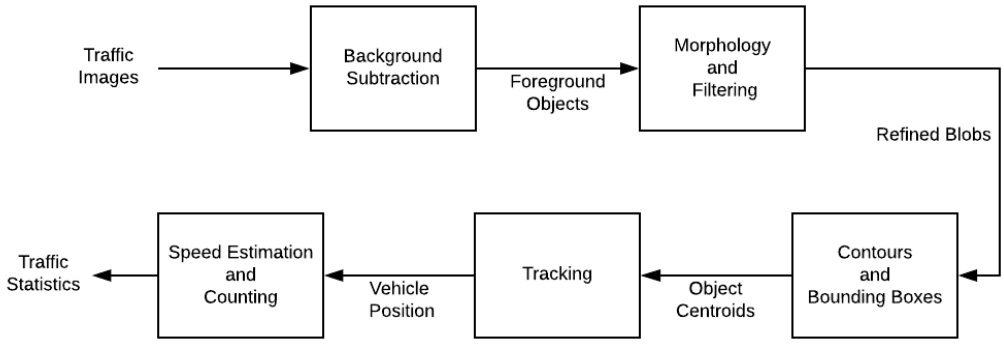


Figure 3.2: Subprocess that comprise the detection subsystem.

3.1.1 Background Subtraction

The background subtractor is reposible for determining which pixels are background and which are foreground objects. The subtractor uses a Mixture of Gaussian model (section 2.6.2) to cluster the pixels into those two sets - background and forground. Initially the model is 'trained' on several hundred images - a few seconds of video - so that it's immediate use yields the most accuracte statistics. The software implemntation of a Gaussian mixture model used is OpenCV's BackgroundSubtractorMOG2 function [18]. This implementation is based on the research by Zoran Zivkovic and Ferdinand van der Heijden [19] [20] in which a method of using a Gaussian Mixture Model (GMM) that improves upon former GMM in both speed and effectiveness at segmenting foreground objects, taking only a pixel's intensity as a feature. The subtraction component of the detection process was by far the most complex and thus the most computationally expensive, requiring each pixel in an image to have it's own probability density distrubtion and then to recalculate that for each new image. It was imperative, however, that the algorithm be fast enough that images could be processed as they arrived in real-time so that traffic data could reflect live conditions. Fortunately the speed of this implementation made it a suitable fit for a low power microcontroller and it's effectiveness ensured it's adoption into the system, as can be seen in Figure 3.4. This method is particularly effective at picking up moving objects as they cause pixels to have constantly changing intensities and making it easy for the model to determine that they're not a part of the background.

Notice in Figure **??** the gray pixels in and around the foreground objects, these are shadows that the OpenCV's GMM implemetation can explicitly detect. They are removed by thresholding (equation 2.3) values that are not white and converting them to black (background) pixels.

3.1.2 Morhpology and Filtering

After isolating foreground objects it's necessary to remove noise and consolidate larger entities so that the only foreground pixels encountered by proceeding processes comprise vehicles. Because the GMM clusters pixels based on their value changes in lighting which might be caused by a cloud moving or a cars shadow among other others, can change the intensity of a background pixel and make it look like it's a foreground pixel. Furthermore, darker pixels, in car windows in particular, can make them appear like the road and hence background pixels, resulting in fractured foreground objects where only a single entitity should exist as in Figure 3.4.

Filtering

The noise generated by spurious foreground pixels looks a lot like salt and pepper noise and so to deal with this a median filter is applied to remove it (see Section 2.3.1). The effect of this can be observed in Figure **??**. It's important to remove this noise because it's evidently not a vehicle and will complicate proceeding image processing.

Morphology

The foreground objects presented at this point are mostly correct and whole however some are fractured due to their windows reflecting the same color as the road. To consolidate these fractured entities an opening, closing and dilation (section 2.4) are performed, as can be seen in Figure **??**.

In determining the calibration of each

3.1.3 Countours and Bounding Boxes

Contours formally identify a foreground object by identifying the coordinates of their perimeter. Figure 3.3 shows the contour outlines of each foreground object from 3.4f which were located by using OpenCV's findContours function, which is based on the algorithm by Satoshi Suzuki [21]. Taking pixels at the extremities in the x and y direction for each contour is used to form bounding boxes as in Figure 3.4f. Bounding boxes can be used to determine the area, height, width and location of an object, which are important properties when trying to determine if an object is a vehicle, furthermore they store and compute more cheaply the irregular polyon of a contour. The bounding box dimensions and location are generated by the OpenCV function boundRect which takes a contour as a parameter and returns a bounding box's up-right rectangular contour, that is the top left corner coordinate and the box's width and height.

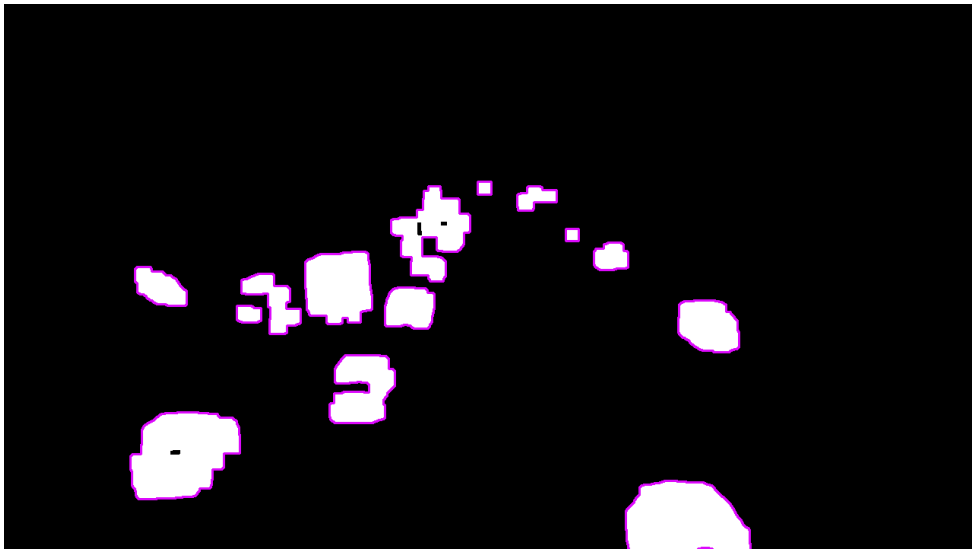


Figure 3.3: Contours outlining foregroung mask objects.

3.1.4 Tracking

It is neccessary to track the foreground objects to measure their speed and position. Each object's location in an image is determined by a centroid calcuated from their respective bounding boxes. A list of centroids is maintained and new centroids are calculated for

each new image, if a new centroid's position is sufficiently close to an old centroid it is assumed to be the new position of that old centroid. Furthermore, if a new centroid is not found for an old centroid in a new image frame then that old centroid has a limited amount of frames before it is dismissed which can occur if it's object leaves the frame is occluded by another object or otherwise is no longer being recognised as a foreground object by the detection process. These latter situations can arise if the view of a vehicle is blocked by another, if the vehicle is shadowed by another making its pixel values darker and more similar to the background or if the vehicle is stationary the GMM will begin to update itself perceiving these unchanging pixels as background. Generally these scenarios do not cause a problem if the system is calibrated correctly and the camera angle is favorable and pertaining to the situation of vehicle being stationary once they begin to move they will be recognised as vehicles once more. In Figure **??** the centroids are visualized on the objects along with a unique identifier which is used to mark ownership of a foreground object. This design was based heavily on the work of Adrian Rosebrock as outlined in his tutorial series on PyImageSearch [14][15].

3.1.5 Counting and

3.1.6 Calibration

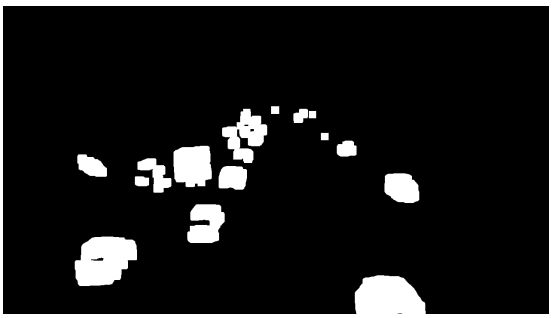
It is unfortunate but neccessary that for this method of vehicle classification that for each different location and camera angle an element of calibration is required to obtain best results. This is a function of the size of vehicles in the camera frame and the lighting conditions at the location. Presently these factors are compensated for by manually calibrating the morphological operations and areas of interest for counting and speed measurement.

(a) Img: Andrey Nikishaev.

(b) Background subtractor output.

(c) Shadows thresholded.

(d) Median Filtered.



(e) Morphologically altered.

(f) Bounding Boxes.

Figure 3.4: Stages in the computer vision detection process.

Calibrating Morphological Operations

To find the optimal morphological structuring element shape and size, and the number of iterations of closing and dilation to perform for the setting in Figure 3.4a a visual analysis of the effect of a number of settings was performed. For example Figure 3.6 show the result of a morphological closure to the output of the background subtractor using different structuring element shapes and closure iterations. 7x7 was formerly settled on as the structuring element size for it produced not too much nor too little effect on the foreground objects. In the visual analysis you seek the result that has converted the most fractured vehicle masks into a single closed contour wit the least iteration, hence for this particular example the optimal morphological closure parameters were a rectangular structuring element with 3 iterations. In Figure 3.5 the highlighted shapes have found closure and so will be counted as a single entity in the contouring process.

(a) Rectangular structuring element closure

(b) Elliptical structuring element closure

Figure 3.5: Comparison of morphological closure using a 7x7 rectangular and elliptical structuring element for 3 iterations.

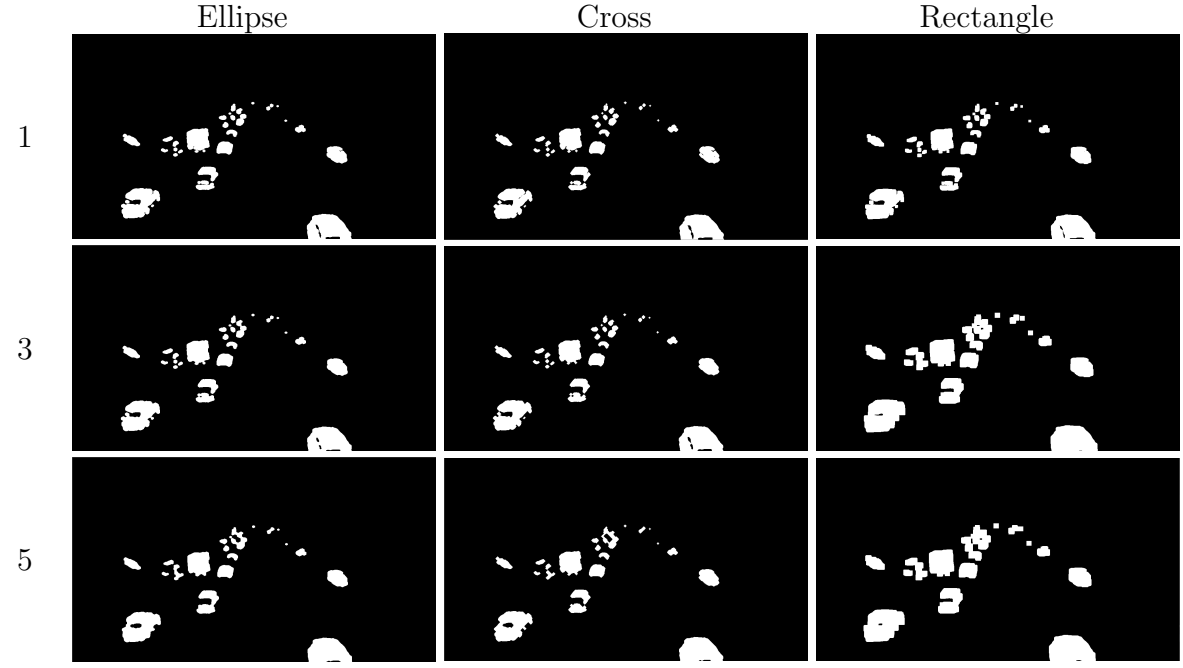


Figure 3.6: Morphological closing using different 7x7 structuring elements and iterations.

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