CELLULAR POSITIONING IN WCDMA NETWORKS USING PATTERN MATCHING

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DECLARATION

I declare that this dissertation is my own unaided work. This thesis is being submitted in fulfillment of the academic requirements for the degree of Master of Science in Engineering in the Faculty of Engineering and the Built Environment at the University of Witwatersrand. It has not been submitted for any other degree or in any other university.

Signed:

…………………………………

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ABSTRACT

Cellular positioning has opened the doors for various creative technological expansions in the field of Location Based Services, in addition to the safety function that it allows for. Despite the significant advances in cellular positioning, the developing and third world countries are being left behind. Better levels of accuracies are required in these nations where the majority of the population cannot afford GPS-enabled phones.

The pattern matching technique is focused on in this research. It involves studying signal patterns from the Base Stations to a mobile phone, to obtain fingerprints at each reference location to form a database. During the location estimation process, the observed fingerprint is compared with the database, and a subsequent match is made. The primary advantage of this technique is that high accuracies can be achieved with minimal costs.

This research focuses on studying the efficiency and accuracy of various pattern matching techniques which are investigated in both WCDMA and GSM networks in suburban areas in South Africa. Since certain areas have predominantly GSM coverage, it is necessary to include GSM network in this research. In addition, the inclusion of both GSM and WCDMA network data can be beneficial as it provides further criteria for correlation.

Field measurements are carried out to obtain the Radio Frequency measurements that are needed to construct the database. Various methods are analyzed and enhanced to obtain better levels of accuracies during the correlation process of the pattern matching procedure. This includes investigating the effects of penalty terms, weights, map matching, Exponential and Least Means Square approaches, as well as the use of measurements from GSM, WCDMA, and the combined networks.

High levels of accuracies were obtained and it can be concluded that these techniques do work in a suburban area, irrespective of its geographical location. The literature study shows that some of these pattern matching techniques would also yield good results in urban areas, while other techniques are more suitable for rural areas.

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LIST OF ABBREVIATIONS

3G	Third Generation
AGPS	Assisted Global Positioning System
AOA	Angle of Arrival
BCCH	Broadcast Control Chanel
BS	Base Station
BSC	Base Station Controller
BSS	Base Station Subsystem
BTS	Base Transceiver Station
CDMA	Code Division Multiple Access
CERP	Circular Error Probability
CI	Cell ID
CID	Cell Identification
CPICH	Common Pilot Channel
DBF	Discrete Bayesian Filter
DCM	Database Correlation Method
DS/CDMA	Direct Sequence Code Division Multiple Access
E-OTD	Enhanced Time Difference
FCC	Federal Communication Commission
GDFS	Global Data File System
GMLC	Gateway Mobile Location Centre
GPRS	General Packet Radio Services
GPS	Global Positioning System
GSM	Global System for Mobile communication
HLR	Home Location Register
HSPA	High Speed Packet Access
IPDL	Idle Period Downlink
kNN	k-Nearest Neighbour
LAC	Location Area Code
LBS	Location Based Services
LCS	Location Services
LEAN	Learn Another
LMU	Location Measurement Unit
LOS	Line of Site
MLE	Maximum Likelihood Estimate
MM	Map Matching
MS	Mobile Station
MSC	Mobile Switching Center
Narf	Neighbouring ARFCN
NLOS	Non Line of Site

NN	Nearest Neighbour
NMR	Network Measurement Report
Nrxl	Neighbouring Received Signal Strength
NSS	Network Switching Subsystem
OTDOA	Observed Time Difference of Arrival
PCM	Pilot Correlation Method
PDP	Power Delay Profile
PNC	pseudorandom number code
Q	Penalty Term
RMSE	Root Mean Square Error
RNC	Radio Network Controller
RSCP	Received Signal Code Power
RSSI	Received Signal Strength
RTT	Round Trip Time
RxLev	Received Signal Level
Rxls	Received Signal Strength
SC	Scrambling Code
SMLC	Server Mobile Location Centre
SMS	Short Message Service
SRNC	Serving Radio Network Controller
SVR	Support Vector Regression
TA	Timing Advance
TAE	Trimmed Average Estimate
TDOA	Time Difference of Arrival
TOA	Time of Arrival
Uarfc	UMTS absolute Radio Frequency Channel Number
UE	User Element
UMTS	Universal Mobile Telecommunications System
WAE	Weighted Average Estimate
WCDMA	Wideband Code Division Multiple Access
WkNN	Weighted k-Nearest Neighbour

1. Introduction

1.1. Background

Cellular positioning refers to the process of locating a mobile user by utilizing Radio Frequency signal measurements. In addition to the many Location Based Services such as requests for restaurant information by a mobile user or warnings about weather conditions, accurate positioning is also essential for emergency purposes. For this reason, the release of the U.S. Federal Communication Commission report in 1999 resulted in a need for further study regarding this topic [1]. This report required all cellular network operators to be able to provide information on a mobile user's location for safety reasons to an accuracy level of 100m for 67% of the cases and 300m for 95% of the cases for a network based method. A possible solution is to incorporate GPS technology into cellular phones. However, particularly in a developing or third world nation, it is impractical and expensive to expect every cellular phone to be replaced.

Various common methods used in cellular positioning exist. Cell Identification produces accuracies dependant on the cell size and is used in environments where high levels of accuracies are not needed, such as restaurant enquiries. The Time of Arrival and Time Difference of Arrival techniques require clock synchronization, which can be obtained by using more stable clocks, which in turn results in hardware changes leading to higher system costs. In addition to it requiring the installation of antenna arrays at the base stations (BS), the Angle of Arrival method yields poor accuracies in Non-Line of Site conditions. Although hybrid positioning technologies generally yield higher accuracies, they require greater processing power and higher network costs.

In a perfect environment with Line of Site and no multipath propagation, it is possible to obtain excellent levels of accuracies using these abovementioned techniques. However, in reality phenomena such as multipath propagation are unavoidable. For this reason, the pattern matching technique is studied further and implemented in this research since it still produces good results in these conditions.

1.2. Subject of Report

This research focuses on improving the accuracies of cellular positioning in a developing country. A method which will cater for the poorer parts of the population that cannot afford GPS-enabled phones needs to be studied and improved. At the same time, this method must cater for the rest of the population that choose to disable the GPS function on their phones due to its shortcomings such as high power consumption.

Cellular positioning using pattern matching is also known as Database Correlation Method and involves studying signal patterns from the BS's to a mobile phone, to obtain "fingerprints" at each reference location. These "fingerprints" together with its corresponding location forms the database. During the location estimation process, the observed "fingerprint" is compared with the database, and a corresponding match is made. The primary advantage of this technique is that high accuracies can be achieved with minimal costs. In addition, it allows for flexibility since the accuracy can be improved by just improving the model. This is in contrast to geometric based technologies which require more accurate measurements to be taken, to improve the accuracy. In addition, pattern matching requires no changes to be made to the user handsets, while no major changes need to be made to the network architecture which means that it can be implemented much faster.

For these reasons, this research concerns the use of pattern matching as a means for cellular positioning in a suburban environment in a developing country. It needs to be tested to ensure that it will work in any suburban environment with similar environmental conditions, irrespective of its geographical location. Research performed in [25, 26] shows that urban areas see the best results for the pattern matching method. Thus, the tests carried out in a suburban area will give an indication as to whether the techniques tested in this research will work in an urban area as well. This process is aided by several techniques that enhance and optimize the positioning procedure. This includes the use of penalty terms, weights, map matching, as well as the influence of exponential and Least Means Square statistical analytic approaches. These approaches are applied to the cost function which is used to correlate the sample and database fingerprints. Information on the BS's or Node B's available in a rural area will give an indication as to whether these techniques will work in a rural environment. The use of measurements from Wideband Code Division Multiple Access (WCDMA), Global System for Mobile Communication (GSM) and the combined networks is also analyzed.

On another note, all four cellular operators in South Africa have implemented 3G technology and the number of subscribers is growing rapidly. Thus it is essential to develop better methods of estimating the location of a mobile user in this network as well, while still considering those that cannot afford 3G handsets yet.

1.3. Objectives of Report

The objectives of this research are therefore to:

- Research the various techniques used during the pattern matching process.
- Determine which Radio Frequency signal measurement parameters will be the most beneficial.
- Investigate and develop different algorithms to improve the accuracy of the correlation process in the pattern matching procedure.

- Determine how the cost function can be created and modified to improve the accuracy?
- Determine whether clustering will produce significant improvements in the results.
- Analyze and implement methods of reducing the errors obtained by the GPS measurements which are needed to obtain the location parameter for the database.
- Test these algorithms in suburban environments.
- Analyze the effects of several location estimates that may be obtained for a particular sample.
- Determine if these techniques will work in any suburban environment, irrespective of its geographical location.
- Determine if the dominance of either a GSM or WCDMA network in the area will affect the results considerably.
- Establish whether the use of both GSM and WCDMA data in the pattern matching process will provide better results.
- Draw conclusions on the effectiveness and feasibility of actually implementing the techniques in reality.
- Recommend any improvements that can be made to improve the efficiency and accuracy, based on these conclusions.

1.4. Scope and Limitations of Investigation

This research focuses on testing the effectiveness of the pattern matching procedure in a suburban environment. All other factors which could influence the results had to be kept constant. These include the weather, service provider and type of environment. However, comparison with research done previously and details on the Base Stations or Node B's available in these environments will provide information to determine whether these techniques have potential to work in a suburban or rural area.

1.5. Plan of Development

The structure of this thesis is as follows:

- Chapter 1 provides an introduction to the thesis.

- Chapter 2 is a detailed explanation of the literature that was surveyed. This chapter provides the reader with information on the various methods of cellular positioning that exist, as well as on the advantages and disadvantages of each of them. This chapter also motivates the choice of pattern matching as the method chosen in this research for cellular positioning. The network architecture involved to accommodate LBS is also briefly explained.

- Chapter 3 describes the key questions addressed in this thesis. It also includes the methods followed to obtain the test data as well as the processes and analyses techniques performed.

  Two suburban areas with similar scenarios were chosen to carry out the field tests. Measurements from both the WCDMA as well as Universal Mobile Telecommunications System (UMTS) networks were recorded. A Sony Ericsson phone was put into Field Test Mode and used together with a Garmin GPS device to obtain these measurements.

  Various methods were studied and enhanced to obtain the best possible accuracy levels. Rural areas can generally only detect the serving cell at any location point. For this reason, a Least Means Square approach based on the serving Cell ID (CI) alone was analyzed. The effect of clustering these serving cells was also analyzed to try to eliminate any outliers. The use of the serving CI as well as the neighbouring CI's will provide more parameters for the correlation procedure. Techniques carried out that use all the detected CI's include the Common CI's approach, Penalty Term approaches as well as the use of weights in these Penalty Term approaches, which all use a Least Means Square approach to calculate the cost function. The use of an exponential cost function as well as a Multiple Weights approach both make use of an exponential cost function to correlate the sample and database fingerprints.

The GPS device has accuracy levels of up to 15m [27]. To cater for any errors produced by the GPS, a map matching procedure is used to match the measured GPS coordinates to a digital map.

- Chapter 4 gives a detailed analysis of the results obtained using the various techniques in GSM and WCDMA networks. These results are then summarized and compared with the results obtained in the literature survey.

- Chapter 5 draws conclusions, based on the findings. This chapter is then concluded with the key finding that the best result in terms of both reliability and accuracy was the Single Penalty Term Approach. The inclusion of weights in the cost function of the Penalty Term approaches appeared to show no harm and only strengthened the cost function. On the other hand, the clustering approach has potential of yielding relatively good results in rural areas, since generally only the serving cell is measured in this environment. Recommendations are also made for future research that can improve the results.

2. Literature Review

2.1. Background on Cellular Positioning

2.1.1. Motivation for Cellular Positioning

The subject of cellular positioning has become very popular due to the many advantages that it offers in terms of Location Based Services and the increasing public interest in this field. In simple terms, cellular positioning refers to locating a cellular phone and its user by utilizing the Radio Frequency signal measurements.

The need for greater study into cellular localization was motivated with the release of the Federal Communication Commission (FCC) report in 1999. This report required, for safety reasons, that all cellular network operators be able to provide location identification of mobile stations, by the year 2001 [1].

Table 1 indicates the minimum accuracy levels required by the FCC. All network-based positioning techniques require a minimum accuracy level of 100m for 67% of the estimations made, and a minimum accuracy of 300m for 95% of the estimations that are made. Similarly, mobile-based positioning methods must have accuracies of at least 50m in 67% of the cases, and 100m for 95% of the cases.

	Accuracy Level	
	67% of calls	**95% of calls**
Network-based	100m	300m
Mobile-based	50m	100m

Table 1: Accuracy levels required by the FCC [4]

The FCC ruling requires that localization techniques work with existing cell phone networks, such as Global System for Mobile communication (GSM), General Packet Radio Services (GPRS) and Code-Division Multiple Access (CDMA). One possible solution is to incorporate GPS into cellular phones. However, it is impractical and expensive to expect every cellular phone to be replaced. More realistic and cost-efficient methods, which can be integrated into the existing wireless networks, have been developed and there is a constant need for improvement.

The basic methods of estimating the location of the mobile user include, cell identification and Timing Advance, Time of Arrival (TOA), Time Difference of Arrival (TDOA) and Angle of Arrival (AOA). However, factors such as multipath effects, Non Line of Site (NLOS) and the number of possible averages are serious limitations in such position estimation [3].

The positioning system can be network based or mobile based, depending on the bandwidth of the system as well as the computational capacity of the mobile station. In the case of network based systems, the positioning function and the required computations are given to the network. On the other hand, the positioning function is done in the mobile phone in the case of mobile-based positioning methods.

2.1.2. Applications of Cellular Positioning

The applications of cellular positioning have grown tremendously. Location based services are applications that utilize the position of the cellular user. Generally, location based services can be categorized into push services and pull services. Pull services are requests sent by the mobile user asking for information. These can include functional services such as ordering a taxi or it can be informational services such as information requests for the nearest restaurant or ATM. On the other hand, push services deliver information that was not directly requested by the mobile user. These can be for example subscription services, or emergency warnings, such as dangerous weather warnings. These also include location specific advertisements, such as when a specific shopping complex is entered [5].

In South Africa, the following location based services are examples of those that are currently in use:

- **Vodacom's Look4me**
  This service enables a Vodacom customer to use a mobile phone or the internet to locate someone using a Vodacom number. However, permission needs to be obtained from the other person and their phone must be switched on and within network coverage. This service can be used for example to allow parents to keep track of their children [6].
- **Vodacom's Look4help**
  The Look 4help panic number ('120'888'888#) is saved to speed dial and is pressed in an emergency situation. Four pre-defined people will then be notified that the panic button has been pressed and they will be informed about your location [7].
- **MTN WhereRU**
  This has a similar purpose to Vodacom's Look 4me. If a person's location has been requested, either an SMS with details of their location, or a map of their whereabouts will be sent [8].
- **MTN 2MyAid**
  MTN 2MyAid works in a similar manner to Vodacom's Look4help [9].
- **MiTRAFFIC**
  By sending an sms to a certain number, this service can track down the location of your mobile phone and send you a report of the traffic updates within a 50 km radius of your location [10].

2.1.3. Privacy Concerns

Context based Location Based Services (LBS) involve learning the interests and activities of the user. For example, if the mobile user has visited a cricket stadium, it could also mean that the user is also interested in sports grounds and sports shops. This tends to arouse privacy concerns amongst cellular phone users if their preferences and history are being tracked. To cater for this, the choice to control the privacy should be the user's decision and not the service provider's. The user should be notified if any information is being collected, as well as be given the choice of turning the context based LBS on or off [5].

The 3GPP location services (LCS) requirements include that the mobile user's location must always be available to the service provider. The mobile user should also be able to control the privacy for any value added services. However, in the case of emergency services, the mobile user should be able to be positioned at all times as per local regulatory requirements [11].

In January 2009, there were approximately 26 000 people who were victims of GPS stalking annually, which is a great concern. Many of the top Apple and Google Android smartphone applications send the user's location information to Apple and Google respectively. The user has no control over this or over the companies that obtain the information from distributing it freely to anybody. For this reason, the United States of America released the Location Privacy Protection Act of 2011. The implementation of the bill now requires that any company who obtains the location information of a mobile user must first get the consent of the user before collecting his or her information or distributing their information to a third party [12].

2.1.4. Common Satellite Based Localization Techniques

2.1.4.1. Global Positioning System

Global positioning system is a global radio-navigation system, which utilises 24 satellites placed such that at least 5 are in view from every point on the earth and the controlling ground stations. Most mobile phones today are equipped with GPS functionalities [13].

GPS works by triangulation, which involves the following steps [13]:

1. The GPS receiver measures the distance using the travel time of radio signals.
2. Time is then measured.
3. Time is then converted to distance, thereby determining the satellite locations in orbit.
4. Any delays experienced by the signal during travel, are compensated for.

Three satellites are used in a method called triangulation, or more accurately referred to as trilateration. As shown in Figure 1, the signals of at least three satellites are used to determine the position of the user, carrying the GPS receiver [13].

The time taken for the satellite signal to reach the receiver is determined by comparing the satellite's pseudorandom number code (PNC), which is a code unique to a satellite, with the receiver's PNC. This gives an indication of the signal's travel time, which is then multiplied with the speed of light to yield the distance between the receiver and the satellite [13].

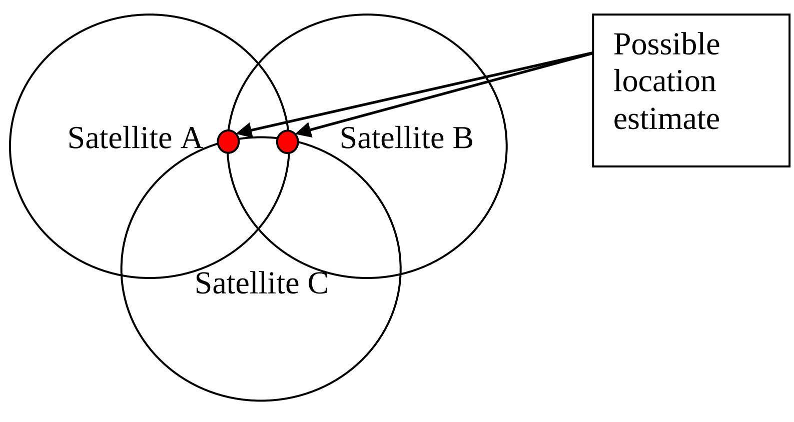

Figure 1: The trilateration process used in the GPS process [13]

Satellites, being almost 17 703 km's away, have to use extremely accurate atomic clocks. Even a tiny error of a few milliseconds in the signal travel time, can result in an error in the calculation of the location by up to 200 miles. On the other hand, a receiver's clock does not have to be as accurate, since any timing errors can be rectified by measuring the distance to a fourth satellite to synchronize its PNC with the satellites. Exact positions of the satellites have to be known at all times. The monitoring stations and ground antennas constantly monitor the satellite's speed, position and altitude, as well as check for any errors due to gravitational pull from the moon, sun and solar radiation pressure. This information is then sent back to the satellites which then change the timing signals accordingly [13].

2.1.4.2. Assisted GPS

Assisted GPS (AGPS) was developed to overcome certain shortcomings experienced by GPS. AGPS is capable of delivering information such as GPS time and satellite orbital parameters to the receiver via cellular networks. GPS cannot function without this information and it poses a big problem in urban areas which have many obstacles. In dense environments, the GPS receiver may not be able to detect all the required number of satellites. Nevertheless, in these situations, the mobile phone can still detect enough Base Stations (BS). Although AGPS requires that the mobile phone have a partial GPS receiver, the calculations are still done in the network. The AGPS server must be able to simultaneously detect all the same satellites as the mobile phone. Thus, the mobile network can accurately determine the location of the mobile phone and convey this information to it [13]. Furthermore, AGPS raises privacy concerns since a third party assistance server has information on the user's location.

2.1.5. Common Land-Based Localization Techniques

Although location estimation exists in South Africa today by certain mobile operators, basic techniques have been used, and thus may not yield the best possible accuracies. The most common methods of cellular positioning have been discussed below.

2.1.5.1. Cell Identification (CID)

This technique works by using the base station to which a mobile phone is connected, to identify its location. The accuracy depends on the size of the cell and can be between 100 meters in urban areas, to 20 kilometers in rural areas. For this reason, this method is used where high levels of accuracies are not needed, such as in climate forecast and restaurant enquiries [16].

2.1.5.2. Signal Strength

Since signal strength is measured in voltage per square area, by making use of this information and the Cell ID together with path loss models, the approximate location of the user can be determined. By using the estimated distances from three or more base stations, the location of the mobile station can be determined. However, this method is dependent on many factors such as terrain and attenuation, which can affect the accuracy greatly [16].

2.1.5.3. CID + Timing Advance (TA) or Round Trip Time (RTT)

Timing Advance is the time taken for the signal to travel between the base station and the mobile phone. Instead of the CID + TA for 2G networks mentioned earlier, 3G networks use Round Trip Time (RTT) instead of TA. TA is used in GSM networks to enable the mobile phone to determine how long in advance it must transmit in an uplink burst, such that it will arrive at the base station at the appropriate time slot. Since the user's distance from the base station is dependent on timing advance, information about the location of the mobile user can be calculated. Thus this information together with the CID can narrow down an area for the user's estimated location as shown in Figure 2. TA is generally a value between 0 and 63. Each step in this TA value corresponds to a step of 550m in distance [15]. This also proves to be a shortfall since any small inaccuracies in the TA measurement can result in large errors in the distance due to this large step size. This method requires no hardware changes, and only some software changes are required in the base stations [13].

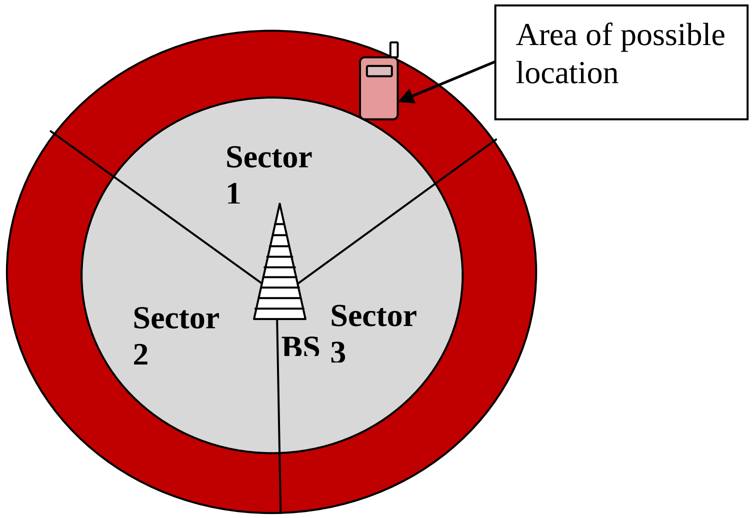

Figure 2: The CID+TA process

2.1.5.4. Time of Arrival

In this method, the time taken for the signal to travel between the base station and the mobile phone is measured. The corresponding distance is equal to the measured time multiplied by the speed of light. Using one base station in the calculation gives an estimate of the user's location as a certain radius around the base station. Using a second base station will constrain the user's location to 2 possible positions, where the two radii meet. A more precise location can be calculated by either using past information about the route taken by the mobile phone, or by using a third base station. Usually, the measured distance is greater than the actual distance due to NLOS error [16]. NLOS errors result when there is no visual line of site between the transmitter and the receiver. NLOS can result in the circles intersecting in more than one point which becomes ambiguous. The Least Squares technique can be used together with redundant measurements to deal with this problem. This technique requires both hardware and software changes to be made in the network and can be very expensive. A further disadvantage posed by this method is that clock synchronization is required, which can be obtained through using more stable clocks such as Rubidium or Cesium clocks. However, this would mean hardware changes, increase in size of the receiver as well as problems related to power consumption. This method is also sensitive to system geometry, and the greatest accuracy is obtained when the circles representing the user's possible location intersect at 90 degrees. This, however, may be difficult to obtain since the mobile user may be constantly moving [14].

2.1.5.5. Time Difference of Arrival (TDOA), Enhanced Time Difference (E-OTD)

This process is illustrated in Figure 3 on the following page. Two base stations can be used to derive a hyperbola with a constant time difference. This hyperbola represents the possible locations of the mobile phone. Thus, the position of the mobile phone can be found by solving the nonlinear equations representing at the least two hyperbolas [16].

$$c \cdot \left(t_1 - t_2\right) = \sqrt{(x_1 - x)^2 + (y_1 - y)^2} - \sqrt{(x_2 - x)^2 + (y_2 - y)^2} \qquad \text{......(1)}$$

$$c \cdot \left(t_1 - t_3\right) = \sqrt{(x_1 - x)^2 + (y_1 - y)^2} - \sqrt{(x_3 - x)^2 + (y_3 - y)^2} \qquad \text{......(2)}$$

In the above equation, t_1, t_2 and t_3 represent the time of arrival of the signal from base stations at positions with coordinates x_1, y_1, x and y represent the coordinates of the mobile phone and *c* refers to the speed of light.

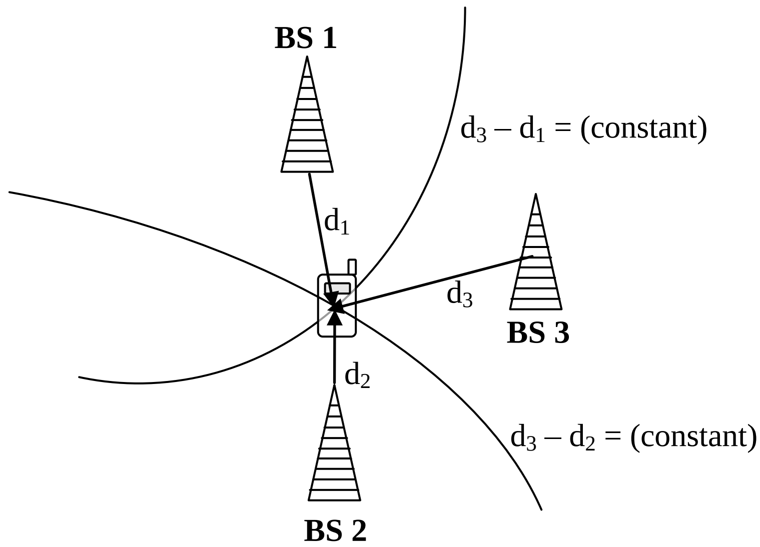

Figure 3: Intersection of hyperbolas in the TDOA technique [15]

Since the hyperbolas are shifted due to positioning errors, they represent a set of nonlinear equations. Methods such as nonlinear least-square, constrained least-square or linearization through a Taylor series expansion are used to solve the equations.

These techniques use the propagation time from three base stations. The method of triangulation is then used to determine the position of the mobile phone. Clock synchronization is required between base stations to be able to calculate the difference in time of arrival [15].

The difference between the E-OTD and TDOA methods is that calculations for TDOA is done by the network provider, while that for E-OTD is done in the mobile device [16]. In addition, the real time differences between BS's are measured by a Location Measurement Unit (LMU), due to lack of synchronization between BS's in GSM networks. E-OTD requires new software in the mobile phones, as well as hardware and software changes at the BS [15].

2.1.5.6. Angle of Arrival (AOA), Direction of Arrival (DOA)

The angle of arrival from a mobile station can be determined by using antenna arrays at several base stations. In the instance where there is no Line of Site

(LOS) component, the antenna accepts a NLOS component, which may not be from the direction of the MS. Thus, it is essential that NLOS identification be incorporated into the system. This technique does not require that the clocks be synchronized. This technique is better suited for macrocells [16].

This method requires LOS to two BS's, and thus may not be appropriate in dense urban scenarios. In 2G networks, this technique has the drawback that antenna arrays need to be installed at each BS. However, in 3G networks, additional hardware may not be needed if adaptive BS antennas are used. In addition, problems with capacity may arise since there has to be co-ordination of the measurements at the different BS's [15].

2.1.5.7. Hybrid Positioning Technologies

Hybrid positioning technologies are usually TOA/AOA or TDOA/AOA strategies. The TOA or TDOA allows for a circular estimate of the position of the mobile user, while the AOA yields a line estimate. Thus, the position of the mobile user can be estimated as the intersection of the circle and the line. As a result, the required number of reference base stations can be reduced from three in this scheme. Studies have shown a significant increase in the accuracy by using this scheme. However, hybrid techniques tend to require greater processing power and higher network costs [16].

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2.1.6. Pattern Matching

2.1.6.1. Introduction

Pattern matching involves studying radio frequency patterns from a mobile phone, including its multipath propagation, to obtain a 'fingerprint'. As can be seen from Figure 4, this 'fingerprint' is then compared with a database, containing locations that have been 'fingerprinted' earlier, and a corresponding match is made to determine the location. Only the position and the signal information need to be stored in the database.

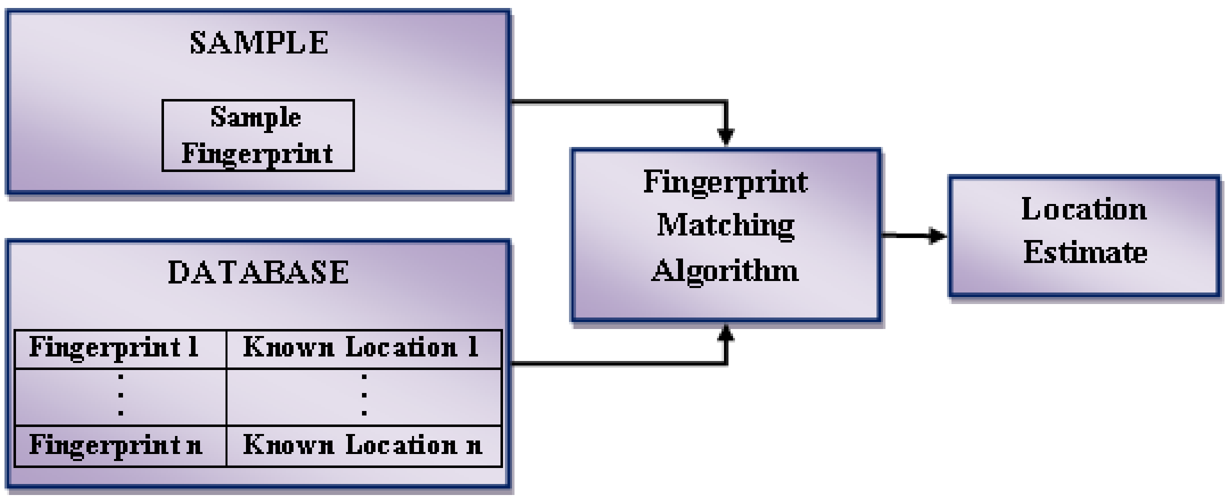

Figure 4: Process used in the fingerprinting method

This is a network based positioning method, which means that it requires no changes to be made to the handsets and can thus be implemented much faster.

The primary advantage of this technique is that high accuracies can be achieved with minimal costs. In addition, it allows for flexibility since the accuracy can be improved by just improving the model. This is in contrast to geometric based technologies which require more accurate measurements to be taken, to improve the accuracy. For example, it may require that time be measured more accurately. This can be very difficult since highly accurate atomic clocks are usually already in use [14]. In addition, there is no large strain that is put on the network since it just requires unexpired Network Measurement Reports (NMR) which are regularly sent from the user element to the base station.

2.1.6.2. Database Correlation Method

Laitinen *et al* [24] introduced the Database Correlation Method using the Least Mean Square approach to correlate the database with the test measurements in a GSM network. The Location Area Code (LAC), Cell ID, Timing Advance and measured signal strength of the serving cell as well as the neighbouring cells are used as the parameters to form the database. The difference, or cost function, is calculated as follows

$$d(k) = \sum_i (f_i - g_i(k))^2 + p(k) \qquad ......(3)$$

where f_i represents the signal strength from the i^{th} Broadcast Control Channel, $g_i(k)$ is the signal strength of the k^{th} database fingerprint and $p(k)$ is a penalty term for those cells that are only detected in either the database or the test fingerprint.

The database fingerprint which yields the smallest value of $d(k)$ corresponds to the best location estimate. Higher accuracies were obtained in the urban environment due to greater variations in signal strength at different points due to reflections off buildings, thus yielding greater diversity in the fingerprints for the correlation procedure. Other factors such as body shadowing would comparatively have less of an impact on the signal strength variations here. Human body shadowing occurs when a human body obstructs the direct path of a signal between the transmitter and receiver. Positioning accuracies of 74 meters for R67 and 190 meters for R90 were obtained. Furthermore, it was concluded that this is the best performing method in dense urban environments where LOS paths are not available.

The initial Database Correlation Method (DCM) for UMTS networks evolved based on that created for GSM networks [33]. Good accuracy results of smaller than 25 meters for 67% and 140m for 95% of the cases were obtained for a dense urban environment. This technique requires the use of multipath delay information from the strongest cell to form the fingerprints. The multipath channels in the network are simulated using the ray-tracing tool to determine the impulse responses. These impulse responses are then used to determine the power delay profile data. Only the strongest cell is used since it has a certain delay in the beginning and one distinct peak. In [32], Ahonen *et al* use both the signal strength and power delay profile measurements to form the database in UMTS networks. The Power Delay Profile (PDP) provides details as to the amplitudes and delays of the multipath components of the signal. To try and remove the interference, the PDP measurements above a certain threshold are used. However, this technique has the disadvantages that the User Element's impulse response measurements are not standardized, and 3GPP does not require such measurement to be sent to the location server. Thus this method requires changes to be made to hardware [23].

2.1.6.3. Advancements in the Database Correlation Method

Zimmermann *et al* [38] uses a Gaussian probability distribution to compute the score and is shown below:

$$S_{EXP} = \prod_{i \in N^*} e^{-\left(\frac{p_i - m_i}{\sigma}\right)^2} = e^{-\frac{\sum_{i \in N^*} \Delta_i}{\sigma^2}} \qquad ......(4)$$

where p_i and m_i represent the predicted and measured values respectively for cell i. The deviation between the predictions and the measurements are represented by σ. The best location estimate is that which corresponds to the highest score. N^* refers to a set of n^* measured cells.

However, this equation penalizes those predicted fingerprints that have a higher number of common cell ID's with the measurements. On the contrary, it is reasonable to say that those fingerprints without common cell ID's have a very low possibility of being the estimate.

Thus, the number of available cells, n^*, is also included, and is given by equation 5:

$$P_{EXP} = \sqrt[n^*]{S_{EXP}} \qquad \text{......(5)}$$

Those cells, n', from the measurement, that do not occur in the prediction and are stronger than the weakest measured test signal, m_{min}, have to be penalized. It is thus used to calculate P_{Pen}.

$$P_{Pen} = \sqrt[n']{\prod_{i \in N'} P_{Pen,i}} = \sqrt[n']{\prod_{i \in N^*} e^{-\left(\frac{p_i - m_{min}}{\sigma}\right)^2}} \qquad \text{......(6)}$$

The final probability used to match the measurements to the fingerprints is thus given by:

$$P = \sqrt{P_{EXP} \,.\, P_{Pen}} \qquad \text{......(7)}$$

Timing advance is not used since GSM only provides a very granular TA value, where each step corresponds to 550m. Accuracies of 607m (R67) and 1021m (R95) were obtained for suburban/rural area.

Shashika *et al* [25, 26] have adopted a cost function which is based on the Least Square Means method, making use of the Manhattan distance and a penalty term. This function is shown below:

$$d(k) = \sum_i (f_i - g_i(k)) + \sum_j |(f_j - I_{max})| \; x \; w_j + \sum_k |(I_{max} - g_k(k))| \; x \; w_k \qquad \text{......(8)}$$

where f_i represents the signal strength from the i^{th} Broadcast Control Channel, $f_i(k)$ is the signal strength of the k^{th} database fingerprint, f_j and g_k represent the signal strengths of those cells that only occur in the test fingerprint or the database fingerprint respectively. The penalty term is represented by I_{max} and corresponds to a signal strength for those cells that are only detected in either the database or the test fingerprint. The contribution of the penalty cell/total number of measurements is given by w_j and w_k. It must be noted that the

Received Signal Strength (RSS) from the serving and neighbouring BS's were used to form the fingerprints at each location.

The location estimation is then done using the Nearest Neighbour (NN) or the Weighted k Nearest Neighbour (WkNN) methods in a GSM network. The NN approach identifies the location fingerprint with the highest $d(k)$ as the estimate. On the other hand, the WkNN approach uses the k nearest fingerprints and estimates the location as a weighted average of these k locations. The weight which obtained the best results is given below:

$$w_i = \left(\frac{1}{d(i)}\right) / \sum_i \frac{1}{d(i)} \qquad \text{......(9)}$$

where w_i represents the weight of the k^{th} nearest fingerprint.

In addition, an approach was analysed where the k nearest neighbours was clustered into 2 clusters geographically, using the K-means method. The weighted average method was then applied to determine the closest cluster with either the most number of neighbours or the maximum weight. These measurements were carried out in a suburban area around the University of Moratuwa, where it was seen that the best results for a suburban area is obtained by the WkNN method.

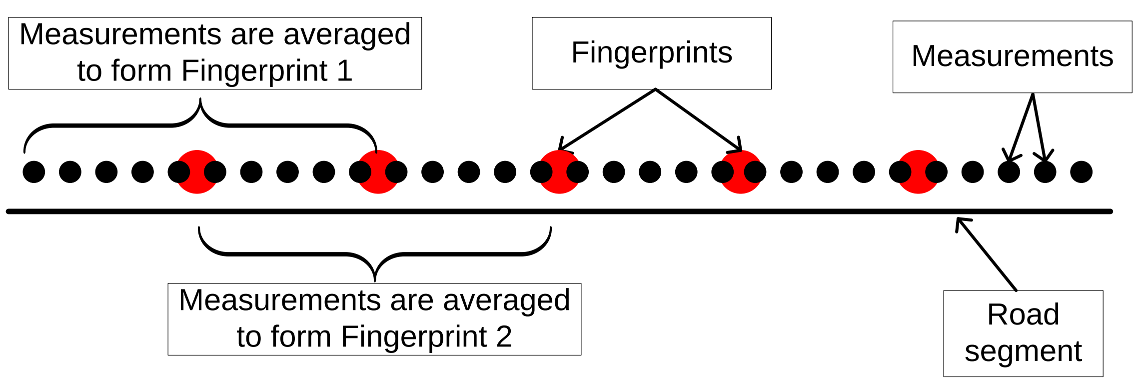

Figure 5: The Sliding-Window method [26]

Furthermore, a "Sliding Window" approach has also been incorporated, whereby consecutive measurements along a path were averaged as shown in Figure 5.

Ten consecutive measurements were averaged and the median of their location points was used as the fingerprint location. Five of these consecutive measurements from fingerprint 1 would overlap with five of the measurements from fingerprint 2. This technique appeared to improve the accuracy compared to using separate measurements for each fingerprint, since it covers those areas in between measurements as well by finding the average of the varying RSS levels.

Mean errors of 100m, 255m and 243m were obtained for urban, suburban and rural areas respectively, while it was discovered that clustering using the K-means algorithm did not provide a significant increase in accuracy.

Kemppi [18] has introduced a penalty term calculation, shown below

$$d(k) = \sum_i (f_i - g_i(n))^2 + \sum_j (f_j - I_{max})^2 + \sum_k (I_{max} - g_k(n))^2 \qquad ......(10)$$

where I_{max} is the penalty term and should be defined for each system depending on, amongst others the receiver sensitivity. Since the function of path loss versus distance tends to stabilize after a certain value of distance, the value of I_{max} can be chosen as the signal strength. The same symbol definitions have been used as is used on page 22.

A second approach to calculating the penalty term, shown below, was also analysed.

$$d(k) = \sum_i (f_i - g_i(n))^2 + \frac{1}{2}\sum_j (f_j - f_w + 10)^2 + \frac{1}{2}\sum_k (g_w - g_k(n) + 10)^2 \qquad ....(11)$$

where f_w is the signal strength of the weakest cell ID in the sample fingerprint and g_w is the signal strength of the weakest cell ID in the database fingerprint. However, the first approach yielded significantly better results.

Kunczier [14, 29], as well as Khalaf-Allah *et al* [28] also make use of past data in the calculation of the present location, via the use of Bayesian networks. Bayesian networks use a directed acyclic graph to represent the conditional independence between variables. Bayesian networks have the advantage that they enable us to make use of incomplete data sets. In addition, causal relationships can be determined. This enables us to better understand the problem during data analysis, as well as to determine the probable outcomes in the presence of interventions. Bayesian networks, together with statistical models enable us to combine prior knowledge with the measured data. This proves to be extremely useful since prior knowledge is usually a scarce component. Bayesian models can be used together with Bayesian networks to avoid the over fitting of data, since models can be smoothed [40].

Kunczier [14, 29] carries out location estimation by using discrete Bayesian networks, where each location point in the database is represented with a Bayesian model which is trained with premeasured data for that location point. The network structure consists of nodes, which contain information about the serving cell ID and neighbouring cell ID's at each position.

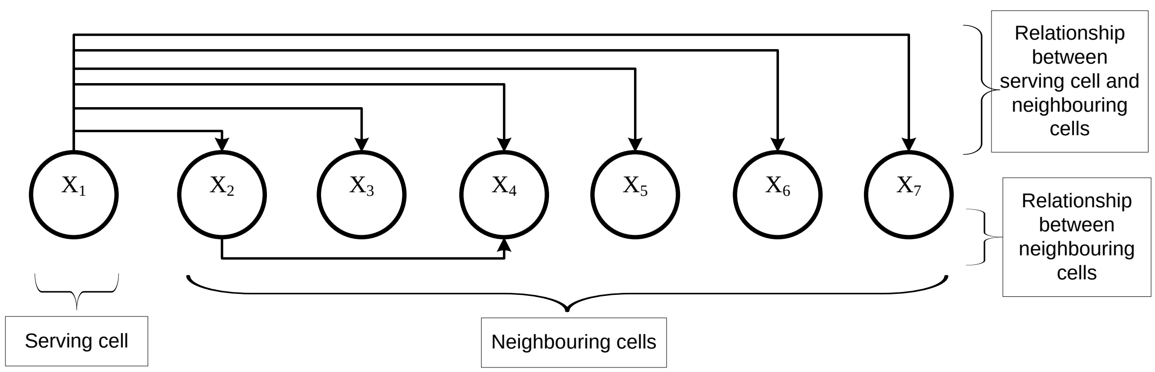

Figure 6: Optimized network structure [29]

Figure 6 above shows an optimized network structure obtained in [29] for the serving cell ID (X_1) and the neighbouring cell ID's (X_2 to X_7). The directed edges represent the probability influence between the cells.

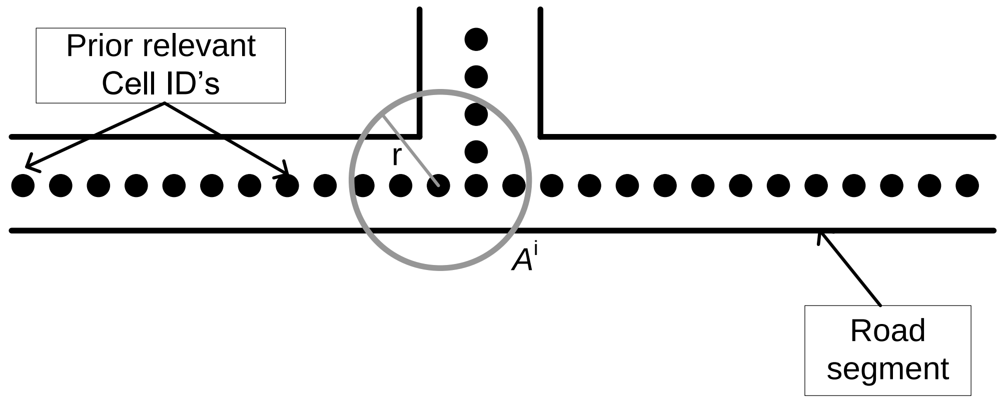

Figure 7: Circled area of interest for prior creation [29]

The prior distribution is created using “expert knowledge” instead of counting past samples. The number of equal realizations is counted in a certain area A^i, with radius r around the current position as shown in Figure 7. This optimal radius is calculated through separate measurements from that which was used to form the database. However, it is only calculated once, and the value is used for the entire area. It was seen that the accuracy obtained from the method using the “expert knowledge” yielded better results when compared to that obtained from using a non-informative prior distribution in which case both expert knowledge and experimental data are not available. In the urban environment, using the prior knowledge which was constructed using “expert knowledge” resulted in errors less than 20m in 67% of the cases, which provides much better results compared to using the non-informative prior [14, 29].

Khalaf-Allah and Kyamakya [28] use a non-recursive Discrete Bayesian filter (DBF) in addition to database correlation to locate the mobile user. Received signal strength has been used to form the database. Furthermore, the TA parameter as well as the serving cell ID is used to limit the area in which the mobile user could possibly be.

Let A be the position of the mobile user and B refer to the data used to form the database. Bayes' theorem gives the relation between the conditional probability of A given B, $P(A|B)$, in terms of the prior probability of A and B, $P(A)$ and $P(B)$, and the conditional probability of B given A, $P(B|A)$. This relation is given below:

$$P(A|B,C) = \frac{P(C|A,B)P(A|B)}{P(C|B)} \qquad ......(12)$$

Bayes' filtering works for environments that are Markovian, which states that the future data is conditionally independent of the past, if the present is given.

A posterior probability density of the MS state at a given time t, over the state space, is referred to as the belief and is given below:

$$Bel(s_t) \; = \; p(s_t|o_t, o_{t-1}, \dots, o_0, m) \qquad .....(13)$$

In (13), the state at time t is given by s_t, while $o_{t\dots0}$ represents the data that was measured from time 0 to time t. The database of measurements is given by m.

The belief is now represented by a set of n weighted samples and is given by:

$$Bel(s) \approx \; \{ s^{(i)}, w^{(i)} \}_{\; i=1,\dots,n} \qquad ….(14)$$

Each sample ($s^{(i)}$) is given a weight ($w^{(i)}$) which reflects the importance that is given to it. The weight $w^{(i)}$), is defined as follows:

$$w(i) \; = \; p(o_t|s_t, m) = \prod_{j=1}^{M} \frac{1}{\sigma RxLev\sqrt{2\pi}} e^{-\frac{(RxLev_j \text{-} RxLev_{DBj})^2}{2\sigma_{\mathrm{RxLev}}{}^2}} \qquad ......(15)$$

In (15), number of observed base stations is given by m. The standard deviation of the measured received signal strength is given by σ_{RxLev}. The measured signal strength from Base Station j is represented by $RxLev_j$, while $RxLev_{DBj}$ is the received signal strength obtained from the database at position $s^{(i)}$.

The location is then estimated using the Maximum Likelihood Estimate (MLE), Weighted Average Estimate (WAE) or Trimmed Average Estimate (TAE) methods which are discussed in more detail below.

MLE takes the sample with the highest weight to be the location estimate, $\hat{s}$.

$$\hat{s} = \mathrm{argmax} Bel(s_t) \qquad \text{......(16)}$$

WAE takes the weighted average of all the samples in the belief, to be the location estimate.

$$\hat{s} = \frac{1}{\sum_{i=1}^{n} w^{(i)}} \sum_{i=1}^{n} s^{(i)} \times w^{(i)} \qquad \text{......(17)}$$

TAE, on the other hand, takes the average of the k highest weighted samples to be the location estimate.

$$\hat{s} = \frac{1}{k} \sum_{i=1}^{k} s^{(i)} \ , k < n \qquad \text{......(18)}$$

The best results were obtained for TAE with an accuracy of 200m for 67% of the cases. This could be because it considers the best posterior data. MAE, being sensitive to noisy measurements, yielded the lowest accuracy.

Singh *et al* [30] introduced a Signal Correlation Method which uses Artificial Neural Networks with the signal measurements from only one BS. Artificial Neural Networks are used to train, learn and predict pattern recognition. Drive tests are carried out to obtain measurements from point A to B (Route 1), from point B to A (Route 2) and then again from point A to B (Route 3) at a slower speed. 12% of Route 1's data is used to simulate Route 2's data using a General Regression Neural Network, forming database A. The estimated and actual locations are compared to determine the error. The worst performing data is then inserted into database A, forming database B. Route 3 is then simulated using database B. The worst performing data from Route 3 is finally inserted into database B. This allows for the Learn-Another (LEAN) process which permits one database's weaknesses to be studied, so that these errors can be catered for.

It was discovered that the use of the LEAN process yielded much better results. Accuracies of 85m for 67% of the estimates, and 291.5m for 95% of the estimates were obtained.

Arya *et al* [31] analyses the effect of parameters such as grid resolution on the performance, in a scenario where the propagation model has been modeled. The normalized correlation coefficient, p, is calculated between the stored and measured RSS vector as follows:

$$p_i = \frac{<s'.s_i>}{\|s'\|.\|s_i\|} \qquad \text{……(19)}$$

The set of scanned BS's in each database fingerprint is given by s_i, while s' represents the scanned BS's in each sample fingerprint. The largest correlation coefficient will then determine the estimated position of the User Element. It was discovered that the improvement of the resolution only really improves the performance in those environments where the errors are low, which can be an idealistic situation.

Borkowski and Lempiäinen [34] have studied a method presented as the Pilot Correlation Method (PCM) and aims to use the standard UMTS terminals. The core advantage of PCM is that it is a purely network-based approach and very few changes have to be made to hardware and software. PCM uses a database containing the most probable Common Pilot Channel (CPICH) levels for each defined positioning region. Positioning region refers to the region in the network coverage, for which each individual entry in the database is associated. Thus, positioning regions are determined according to the requirements of the LBS applications. The accuracy of the PCM is determined by the size and shape of the positioning regions, since it affects the resolution of the estimation. When a request for location is received by the SRNC, a vector with scrambling code ID's and measured Received Signal Code Power (RSCP) of visible pilots is compared with the database. The Least Squares Means method is then used for correlation. The deviation between the stored sample and reported measurement is given by:

$$S_{LMS} = \sum_{i \in N}(s_i - m_i)^2 \qquad \text{……(20)}$$

This deviation is calculated for all entries in the vector N, as well as all the samples in the database. The stored sample and reported measurement are given by s_i and m_i respectively [62]. In order to save computing time, the database is divided according to the scrambling code ID of the first pilot. 67% of measurements were below 70m for urban environments and below 190m for suburban networks, due to larger positioning regions and distances between Node B cells.

Al Hallak *et al* [36] uses Location Area Code (LAC), Cell ID (CI), Base Station Identity Code, Broadcast Control Channel (BCCH) from the serving cell in a GSM network, as well as the RxLev from the serving cell and the 6 strongest neighbouring cells. The Maximum Likelihood formula is used to determine the error, *e*, between the signal information of the request and reference fingerprints.

$$e = \sum_{i=1}^{n}(M_i - L_i)^2 \qquad \text{…...(21)}$$

The measured signal strength and signal strength of the i^{th} database fingerprint on the same Broadcast Control Channel is given by M_i and L_i respectively. The database fingerprint corresponding to the lowest error will then be the best match for the location estimation. The LAC and CI assist in reducing the time for searching through the database. Instead of having to update the database whenever there is a change in the environment or network, they investigate the installation of a grid of radio listeners at selected points between the cells. These radio listeners periodically send Network Measurement Reports to the server that determine the mobile position in the BS, via GPRS or SMS. Thus any changes detected by the radio listeners will allow for a corresponding adjustment of the parameters used.

2.1.6.4. Propagation Models

The database measurements can also be predicted based on propagation models. Even though it is much more efficient with regards to time and effort, it is costly to obtain precise building and topographical data.

Propagation models can either be created empirically or they can be site-specific, in other words deterministic in nature. The empirical models are formulated using information that is measured from the received signal. It is easy to implement, does not require much computation and is not very sensitive to the geometrical characteristics of the environment. Site-specific models, on the other hand, are based on the theory of electromagnetic wave propagation. It requires detailed and accurate information of objects in the environment, and is expensive in terms of computation. Nevertheless, site-specific models are more accurate and reliable [47].

The Okumura model [39] for urban areas was developed from data obtained in Tokyo, Japan. It caters for frequencies of between 150 MHz to 1920 MHz

The Hata-Okumura model [39] simplifies the Okumura model, and is frequently used. It is suitable for networks with large cells, and is not suitable for personal communication systems with cells that have radii smaller than about 1 km [47].

This model caters for the following:

- Frequencies of between 150 MHz to 1500 MHz
- Link distances between 1 km and 20 km

Although the computation time is short for this model, it has the disadvantage that it does not take into consideration the terrain details between the base station and mobile receiver. However, since the base station is usually situated on a hill, this should not pose a big problem. This model also does not take reflection and shadowing into account [49].

Lee's model is used to estimate propagation over a flat terrain. If the terrain is not flat, large errors are expected. Correction factors are included whereby the model can be adjusted depending on the area. [50]

The COST 231 project adjusted the Hata model to cater for the 1.5-2 GHz frequency band, and can thus be used for 3G networks.

The extended Hata model [51] caters for:

- Frequencies of between 150 MHz to 2000 MHz
- Link distances between 1 km and 10 km

Another popular model is the COST 231 Walfisch-Ikegami [51] model. This model assumes that the transmitted wave propagates over rooftops through multiple diffraction. Those buildings that are in line between the BS and the MS are represented by diffracting half screens with equal height and range separation. This model should be used with care when the height of the BS is less than that of the buildings. Research has shown that this model provides a good estimate for propagation with frequencies between 800 MHz and 2000 MHz, as well as for distances between 0.02 km and 5 km. It works best where the base station antenna heights are well above the roof height.

Site-specific models include for example, the Ray-Trace technique and Finite-Difference Time-Domain (FDTD) models. Both these techniques are based on Geometrical Optics, which approximates the propagation of high frequency electromagnetic waves. The image method and Brute-Force method are two example of the Ray-Trace technique. Ray-Trace does not yield very accurate results in environments with complex lossy objects with finite dimensions. [47]

In [38], the Hata-Okumura model was used for suburban/rural predictions. Terrain obstacles have been included in these predictions by using the Epstein-

Petersen Knife Edge model. The propagation predictions for urban areas were done using the Extended Walfisch-Ikegami model, since it produces good results for transmitters on roof tops. Alim *et al* [39] carried out simulations in MATLAB to compare the performance of the Okumura, Hata and Lee models. It was observed that as the BS antenna height increased, the propagation path loss decreased, where the greatest loss was seen to be for the Hata model, and the least loss for the Okumura model. As the user moved the position of the MS antenna further away from the ground, the propagation path loss decreased, with the greatest loss being for the Lee model, and the least loss being for the Okumura Model. As the link distance increased the propagation loss decreased, where the greatest loss was seen for the Lee model, and the least loss seen for the Okumura model.

2.1.6.5. Post-processing Techniques

The GPS device, which is used to determine the location coordinates to which the signal measurements of the fingerprint is allocated, is also prone to errors. GPS accuracies are on average within 15 meters. The factors which can affect the accuracies include ionosphere delays, multipath errors, receiver clock errors, orbital errors, number of visible satellites and satellite geometry [27]. Ionosphere delays result from the propagation of the signal through the atmosphere. Multipath errors are a result of the signal's reflection off buildings and other objects. Receiver clock errors are a result of the fact that the GPS receiver's clock is not as accurate as those used in the satellites. Orbital errors arise from the inaccurate reporting of the satellite's location. The number of visible satellites can be reduced by the signals being blocked by buildings and other large objects. Satellite geometry is a factor since the best accuracies are obtained when the satellites are located at wide angles to each other, while their positioning in a straight line results in poor accuracies.

Kemppi [18] has utilized the Map-Matching technique to cater for any errors in the GPS accuracy.

Post processing is done using a combination of filtering as well as Map-Matching. Map-Matching matches a certain measured location to a location on the digital map of the road, as displayed in Figure 8. The direction of movement can be seen to be from left to right along the horizontal road segment. However, the points in red have been matched incorrectly to the diagonal road segment. Thus, it can be seen that the data of the previous estimated location of the user assists in providing better estimates of the possible current location.

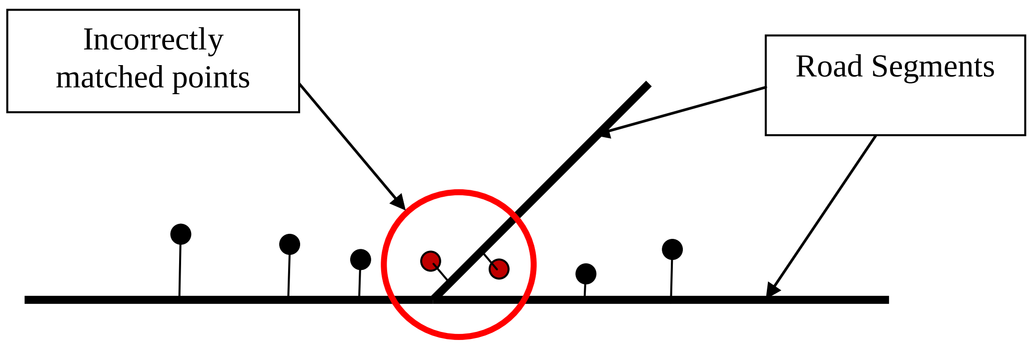

Figure 8: The map matching technique

The following accuracy levels were obtained for the various techniques, indicating that the best method is to use both networks as well as both the post processing techniques [18].

Scenario	R67 [m]	R95 [m]
UMTS	106	379
GSM	68	184
GSM + UMTS	60	162
GSM + UMTS + Kalman	69	118
GSM + UMTS + Kalman + Map Matching	46	99

Table 2: Comparison of the accuracy levels obtained [18]

Gezici *et al* [37] cater for NLOS situations that result in large estimation errors, by applying Support Vector Regression (SVR) to the geo-location problem in a simulated environment. The Kalman Bucy filter is then used to smooth the location estimates obtained after the SVR process. Support Vector Regression involves taking measurements at known locations, in advance, to obtain a training set database. Measurements of the mobile phone are taken and the SVR technique is then used to estimate the location of the user. Structural risk minimization principle is used to minimize the upper bound on the expected risk, instead of the common method of minimizing the empirical risk directly. The SVR method assumes that the training set database is valid, which requires the environment to remain constant. The average error improves from 37.8m, where just the SVR method is used, to 21.1m when the Kalman-Bucy filter is used.

Nypan [45] has implemented a comparison of the performance of the Hidden Markov Model and Kalman Filter as a filtering tool after the DCM process. The states used for the Kalman Filter are position, velocity and acceleration. The noise that occurred in the position and velocity are modeled as first order Markov processes. The acceleration is estimated by the limitations on an average vehicle, while the speed is input into the estimator as a virtual measurement corresponding to the average speed of vehicles in the area under consideration.

It was discovered that the Kalman Filter estimator is sensitive to errors due to variations in speed, such as when there is very slow moving traffic. The Hidden Markov Model, on the other hand, is not as sensitive to minor changes in speed, since the speed is modeled by the transition probability distributions where each state is assigned a speed distribution. A major disadvantage of the Kalman Filter was discovered to be the difficulty in estimating the model parameters compared to the Hidden Markov Model. Hidden Markov Models are statistical models where the states themselves cannot be observed, but instead some probabilistic function of these states is observed. These states can be referred to as hidden states [46].

Nypan [45] considers each state in the Hidden Markov Model to correspond to a position interval on the road.

The state transition probability is given by the following equation:

$$a_{ij} = P\big(q(l+1) = s_j \,|\, q(l) = s_i\big), \qquad i,j \in \{1,2,\dots,N\} \qquad \text{......(20)}$$

where the state at time l is given by $q(l)$, and N represents the number of states. This is the probability that the model will be in state s_j at time $(l+1)$, if the model was in state s_i at time l. This probability is estimated by the speed distribution of vehicles in the required area.

The observation symbol probability distribution is given by equation 22:

$$b_{ij} = P\big(y_p(l) = s_j \,|\, q(l) = s_i\big), \qquad i,j \in \{1,2,\dots,N\} \qquad \text{......(22)}$$

where the state at time l is given by $q(l)$, N represents the number of states, and the observed output at time l is given by $y_p(l)$. This is the probability of measuring state s_j if the model is in state s_i at time l. It is estimated based on the cost functions of comparisons done earlier in the same area.

The next step is to find the optimal state sequence. The Viterbi algorithm can be used for this, since it finds this sequence according to the maximum likelihood [45, 46].

However, the Viterbi algorithm is complex and Nypan [45] has used an alternate approach. The states $q(l)$ are chosen, which are individually most likely to occur at each time l. This has the advantage of maximizing the expected number of accurate individual states.

The nearest neighbour (NN) method is a very straightforward and simple classification method, resulting in very little processing, although it may not necessary yield the optimal solution. This process involves calculating the difference between an unknown test element ‘q’ and the elements in the training data. The element with the smallest difference from ‘q’ determines the class of the test element. However, this method is sensitive to outliers and the best method of distance estimation is not necessarily the typically used Euclidean estimation [19].

On the other hand, the kNN method involves finding the *k* elements in the database that are closest to the unknown element, *q*. From these elements, the majority determines the class of *q* [19].

2.2. Adaptations in the Technologies between GSM and UMTS

Most of the 3G location estimation techniques were adopted from the GSM techniques. The location estimation technologies that have been proposed for GSM networks are CID+TA, TOA, E-OTD and AGPS. Those proposed for UMTS include CID+RTT, AOA, OTDOA and AGPS [20].

The E-OTD approach used in GSM networks has to be adapted to the Idle Period Downlink-Observed Time Difference of Arrival (IPDL-OTDOA) in 3G systems [17]. WCDMA allows Node-B’s to transmit to users on the same frequencies, but encrypted in different codes. For this reason, hearability becomes an issue since it becomes difficult for User Elements to pick up signals from Node-B’s that are very distant. To cater for this, at least 3 Node-B’s are required, but this is not always available. IPDL requires base stations to randomly cease their downlink transmission for short periods of time. When the base station with the strongest signal is not transmitting, the UE can measure the signals from the weaker base stations [21].

2.2.1. Location Services Network Architecture for GSM and UMTS

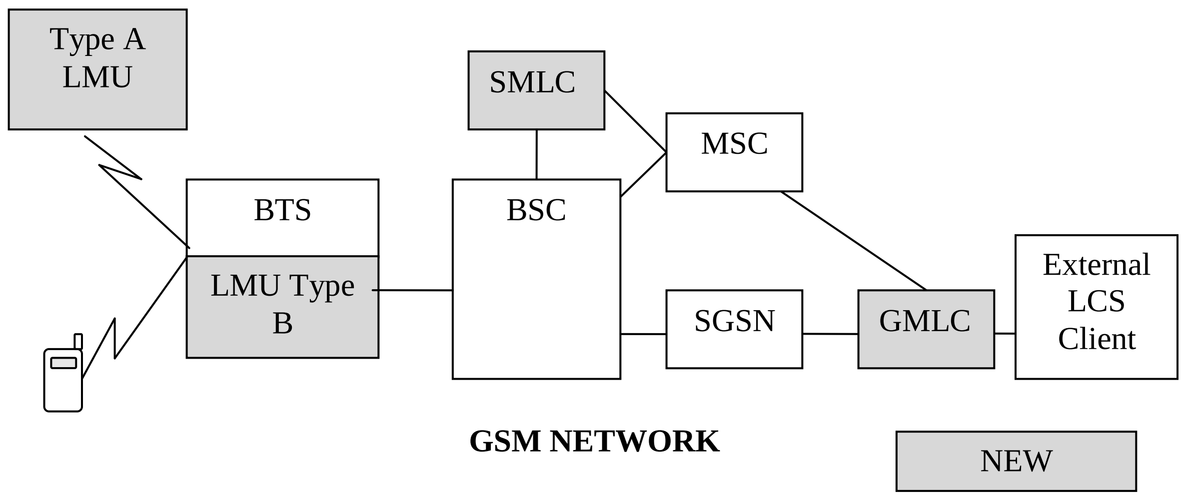

Figure 9: Architecture for Location Services in a GSM network [20]

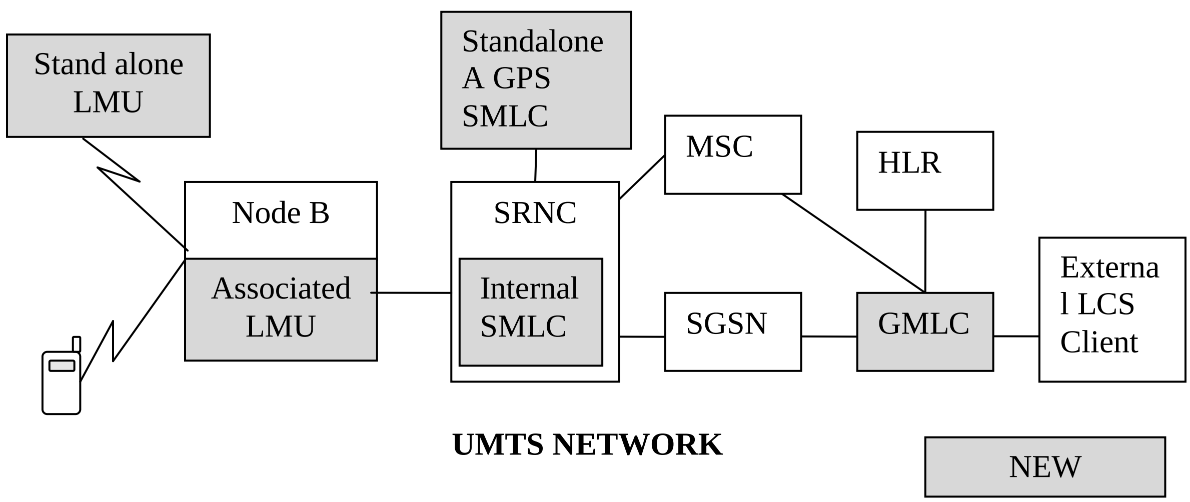

Figure 10: Architecture for Location Services in an UMTS network [20]

Figures 9 and 10 display the architecture for location services in GSM and UMTS networks respectively. Those components that have been shaded in grey are those that have to be added to accommodate location services. A more detailed explanation of these components follows.

The Gateway Mobile Location Centre (GMLC) is the first connection point to a mobile network, from an external LCS client. When a location request is made, the GLMC carries out the registration authorization. It then sends the request to and receives the location estimate from the Mobile Switching Center (MSC) [20].

The Server Mobile Location Centre (SMLC) manages the scheduling and coordination of the resources that are required in the location estimation process, and thereafter calculates the location. In addition, it also controls the Location Measurement Units (LMU) that assist with the location estimation. Two types of SMLC's exist in GSM, namely Network Switching Subsystem (NSS) based SMLC and Base Station Subsystem (BSS) based SMLC. NSS based SMLC's allow signalling to the MSC, while BSS based SMLC's cater for signalling to the Base Station Controller (BSC). In Universal Mobile Telecommunications System (UMTS) networks, the SMLC can be standalone or can be found within the Serving Radio Network Controller, or SRNC (similar to BSS based SMLC in GSM networks). The standalone SMLC communicates to the Radio Network Controller (RNC) and allows for processing of data needed to compute the user's location [20].

The LMU allow for techniques such as TOA or E-OTD. By taking measurements from multiple BS's, it caters for the lack of synchronization between BS's. In GSM networks, Type A LMU's communicate with the Base Transceiver Station (BTS) via the air interface. Type B LMU's may be internal or standalone and communicate with the BSC. In UMTS networks, the standalone LMU communicates with the Node B via the air interface, and the associated LMU, (within Node B), communicates with the RNC [20].

The Home Location Register (HLR) in an UMTS network contains LCS information on the MS's and LMU's [20].

2.3. Performance Measures

2.3.1. Accuracy

2.3.1.1. Circular Error Probability

Circular error probability (CERP) refers to a circle centred at the actual location of the mobile user, which can indicate the location estimate with a certain probability. Generally the radii corresponding to 67% (R67) and 95% (R95) of the estimates are used and this standard is used in the results of this research. Thus for example, a R67 value of 100m means that 67% of the estimates had an error less than 100m. A radius corresponding to 90% (R90) of the estimates is also used in literature.

2.3.1.2. Root Mean Square Error

The Root Mean Square Error (RMSE) is given by the following equation [18]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {d_i}^2} \quad .....(23)$$

Where d_i refers to the measurement error in sample i, and n represents the number of samples. The RMSE complements the CERP, giving an overall picture, but also includes the outliers.

2.3.2. Reliability

The reliability of a positioning technology can be measured by the number of successful estimations with respect to the total number of cases [17].

2.3.3. Availability

Availability can refer to the percentage of time that the user's location can be determined. For example, the GPS method has high levels of availability outdoors, where the satellites are visible to the GPS receiver. On the other hand, as one moves indoors or underground, the availability reduces drastically [20].

2.3.4. Applicability

Applicability refers to the financial and technical aspects regarding matters such as software, hardware, power consumption, processing power as well as standardization issues such as whether the measurements are standardized or not [17].

2.4. Challenges in Cellular Positioning

2.4.1. Environmental

2.4.1.1. Multipath Propagation

Multipath propagation results from reflections of the electromagnetic waves off different objects in its path. Multipath propagation results in fading of the signal, due to the signal arriving at different times and at different angles. Fading has a significant role in those location systems that are dependent on signal strength. This also results in degradation in the hearability of the base stations. The effect of multipath fading can be reduced by using signal strength averaging. Assuming the environment remains constant, the effects of shadowing can be reduced by using pre-measured signal strength contours centered at the base stations [16].

2.4.1.2. Non-line of Site

Non-line of Site (NLOS) error is defined to be the extra distance that the signal travels, compared to the LOS path. Kai [16] attempts to identify NLOS by using the residual ranking algorithm. The residuals are calculated as the square of the difference between the real and estimated distances. The average Gaussian noise in the measurements is usually much lower than the NLOS range error. Thus, the residual can represent the magnitude of the NLOS error.

2.4.1.3. Errors in Measurement Due to Fading

To overcome the effects of fading and errors in measurement in the received signal strength method, Shen *et al* [22] have proposed a fuzzy inference system that has a smoothing function. The system model uses Direct Sequence CDMA (DS/CDMA). To compensate for the shadowing error, training data from actual measurements, or statistical data obtained from simulations. The measurement error is compensated for by giving more importance to the data that has higher measurement accuracy. The fuzzy inference system is one that uses a knowledge base, which utilizes fuzzy interference rules, and an inference engine. The position of the mobile station can then be estimated by using measurement data. Factors such as measurement errors, as well as the propagation environment can be included in the knowledge base

2.5. Summary

In the literature survey that was conducted, it was observed that common land based localization techniques include Cell-ID, OTD, TDOA and E-OTD. Cell-ID yields the lowest accuracy levels, especially in a suburban environment. With this technique, the accuracy decreases with an increase in cell size. OTD (Observed Time Difference)/ TDOA and E-OTD result in better accuracies than Cell-ID. However, the accuracy depends heavily on multipath propagation and may perform very well in dense urban environments [17].

These common positioning techniques generally either require the installation of new expensive hardware or do not yield accurate results. The best results are obtained from AGPS, with GPS providing the next best results. However, particularly in a developing or third world nation, it is impractical and expensive to expect every cellular phone to be replaced.

In ideal conditions with perfect LOS and no multipath propagation, it is possible to obtain good location estimates. However, this is not the case. The Database Correlation Method (DCM), otherwise referred to as pattern matching or fingerprinting, appears to yield very good results and circumvents the multipath problem.

It was noted that although modeling the environment using propagation models saves a considerable amount of time in terms of being easier to create and update, topographical data is expensive to obtain. In addition, the true environment is never perfect and the results obtained using simulations may be a bit too optimistic. For this reason, focus has been given by the author in the methodology section on creating the database using field test measurements instead.

The methodology section will then also focus on the use of weights, as well as the use of clustering and map matching, since they appear to be beneficial in reducing errors. The influences of exponential cost functions, as well as techniques based on least mean squares were analyzed.

To be able to produce a positioning method that does not have a heavy impact on costs, it appears to be wise to use measurements that are already present in the NMR. For this reason, this research will focus on the signal strengths obtained from the various networks, and not on power delay profiles to form the database.

From the research conducted, it appears that the use of both UMTS and GSM data assists the correlation process to obtain higher levels of accuracies. Kalman Filters appear to be beneficial in smoothing the location estimates in route tracking. Bayesian techniques also appear to provide good levels of accuracy. However, Kalman Filtering requires observations over time. Similarly, Bayesian methods also require estimations over time where a number of fingerprints have to be collected and the estimate is made based on both the current as well as the previous fingerprints. For this reason, this research has focused on location estimation and not on route tracking, since route tracking requires that factors such as prior location have to be kept track of and thus is not efficient in terms of memory and processing.

Even though Map Matching requires the availability of past data to obtain the best results, it can still be carried out with only the present data. It must thus be determined whether this approach still produces sufficiently good estimates, with minimal incorrectly matched location points.

3. Key Research Questions and Methodology

3.1. Introduction

The aim of this project was to develop and study accurate methods of location estimation for mobile phones in a developing country such as South Africa. The Oxford dictionary [59] defines a developing country as “a poor agricultural country that is seeking to become more advanced economically and socially”. In the context of this research, a developing nation is one which has already implemented 3G technology. The majority of the population cannot afford the expensive GPS enabled phones. However, there is still a significant part of the population which own 3G handsets and this number is growing rapidly. A method which caters for the poorer part of the population that cannot afford GPS-enabled phones, as well as provides good levels of accuracy for the rest of the population who prefer to disable the GPS function on their phones, due to the previously mentioned shortcomings such as high rates of power consumption, is needed. In addition, between 2009 and 2010, there was a 64.1% growth in WCDMA subscribers in Africa [52]. It is essential to develop better methods of estimating the location of a mobile user in this network, while still catering for the poorer parts of the population that cannot yet afford 3G handsets.

This project focused on analyzing the different techniques used to correlate the test fingerprints to the database fingerprints in the pattern matching process for a suburban environment. Statistics South Africa [60] describes a rural area to be “farms and traditional areas characterized by low population densities, low levels of economic activity and low levels of infrastructure”, while urban areas are described as “formal cities and towns characterized by higher population densities, high levels of economic activities and high levels of infrastructure”. A suburb is defined as “areas within a town or city proclaimed or set aside mainly for residing purposes”. The suburban areas in which the tests are carried out in this research can further be defined to comprise of single storey houses and dense foliage.

The database was generated in a suburban environment of Lynnwood in Pretoria as well as in a similar environment in the SE1 suburb of Vanderbijlpark. The results obtained would provide an indication as to whether these methods will work in any suburban area, irrespective of its geographical location.

It was initially agreed that a leading telecommunications company in South Africa would carry out the field test measurements using engineering handsets. However, towards the end of 2010, these had still not been purchased. To continue with the field tests in time, a Sony Ericsson phone was configured and set to field test mode to obtain the readings. However, the measurement of data using a phone put into field test mode was proved to be time consuming. To find a productive compromise between time and the number of tests carried out, the tests were limited to suburban areas, as previously mentioned. These results could then be compared to tests carried out in other research and if similar results were obtained, an estimate can be made of whether the techniques would be feasible in other environmental conditions.

The influence of map matching on the results was also studied. The aim was to improve the results by correcting the smaller errors due to inaccurate GPS measurements.

The results of the different techniques were analyzed based on the average error, as well as on R67 and R95 errors which can then used to determine whether it meets the FCC requirements.

Thus the key research questions are:

- Study and construct various algorithms of the correlation process in the pattern matching procedure to obtain better accuracies.
- What network measurements or features are necessary to provide pattern matching with good accuracies?

- How can the cost function be constructed and altered to improve the accuracy?
- Will clustering the fingerprints help to eliminate outliers?
- Test these algorithms in suburban environments.
- Although 3G is deployed in South Africa, there are some areas which are not covered. Thus both GSM and WCDMA networks must be analyzed, and in those cases where both will be detected, what is the advantage or disadvantage of using both networks?
- Will the predominance of either GSM or WCDMA in the particular area affect the results greatly?
- Will these techniques work in any suburban area, irrespective of its geographical location?
- Do the techniques have potential to work in an urban or rural area?
- If several location estimates are obtained, how will these be analyzed further?
- GPS measurements are required to obtain the location parameter to which the RF signal measurements will be associated in the database. Thus how can the errors originated by GPS measurements be eliminated?
- Determine how effective and feasible it will be to implement the techniques in reality.
- Based on the conclusions obtained, recommend any future improvements that can be made to produce better accuracies.

3.2. Obtaining Test Data

Test data were obtained by carrying out drive tests. The area under consideration was divided into ‘pixels’ or grids, and measurements were obtained for these ‘pixels’ while driving along these routes. A Garmin Nüvi 205 GPS was used to obtain location measurements. Therefore each pixel in the database contained information on the latitudinal and longitudinal GPS coordinates, GSM cell information, measurements of neighbouring GSM cells and WCDMA cells.

A Sony Ericsson K810i cell phone was put into field test mode to obtain the required measurements. This mode yielded similar measurements to that of many other commercial programs. The older phones could enter the Field Test Mode by just entering a code on the phone. However, newer phones have the Field Test Mode disabled in order to avoid misuse. A modification of the Global Data File System (GDFS) is required to activate it in these phones. The phone is connected to the laptop and the XS++ [41] software tool was then used to modify the GDFS.

The 6 WCDMA channels with the strongest signal, as well as the GSM cell information were measured. The GSM neighbouring channels were also monitored. The phone picked up signals from the WCDMA Node-B’s in some areas and from GSM towers in other areas.

The drive test is conducted at a speed of approximately 20km/h and the measurements are taken at roughly every 15 to 20 seconds. Thus, the measurements are taken with a spacing of approximately 100 meters.

The first set of measurements was taken in Lynnwood (Pretoria). An area of 1.94km^2 was covered as shown in Figure 11 displayed on the next page.

Figure 11: The area covered in Lynnwood, Pretoria (Area A) [48]

Figure 12: A view of a typical street where the field tests were carried out in Lynnwood (Area A)

The second set of measurements was taken in the SE1 suburb in Vanderbijlpark. The measurements for the test samples were taken on the second day, in similar conditions. An area of 1.64 km^2 was covered, as can be seen in Figure 13.

Figure 13: The area covered in SE 1, Vanderbijlpark (Area B) [61]

Figure 14: A view of a typical street where the field tests were carried out in Vanderbijlpark (Area B)

Figures 12 and 14 are images of a typical street in Area A and Area B respectively. This indicates that both the areas are residential suburban areas with no tall buildings, and dense foliage. The database and sample measurements were taken in the earlier hours of the morning, with very little traffic in the area and with sunny weather conditions. The sample measurements were carried out in similar conditions on a separate day. Thus the field tests in Area A and Area B took a total of 4 days to cover.

Figure 15: WCDMA Coverage in Area A [58]

Figure 16: WCDMA Coverage in Area B [44]

In Figures 15 and 16, the areas shaded in red indicate the regions with WCDMA coverage. Thus it can be seen that Area A has predominantly WCDMA coverage, while Area B has predominantly GSM coverage.

3.3. Extracting the Data

All the measurements observed during the field tests are explained in Appendix A. However, for the purpose of this research, only the received signal levels and CID's of the serving GSM cell, GSM neighbours, as well as that of the serving WCDMA cell and WCDMA neighbours were used. These parameters are explained in Table 3 which is given below.

Category	Symbol	Explanation	Possible values
GSM Cell	Rxls	Received Signal Strength	
	Ci	Cell ID	
GSM Neighbours	Narf	Neighbouring ARFCN	
	Nrxl	Neighbouring Received Signal Strength	
	UARFC	UMTS Absolute Radio Frequency Channel Number	
	RSSI	Received Signal Strength	
WCDMA	W	WCDMA cell type	S: Serving cell A: Active set member M: Monitored neighbour D: Detected neighbour
	SC	Scrambling Code	
	RSCP	Received Signal Code Power	

Table 3: Explanation of the symbols used in the GSM Cell section

It must be noted that the Neighbouring ARFCN and Neighbouring received signal strength of the 6 GSM neighbours, as well as the WCDMA cell type, UMTS absolute Radio Frequency, Scrambling Code and Received Signal Code Power for the serving WCDMA cell and the 5 WCDMA neighbours were measured.

The most common antenna configuration for a UMTS network include omnidirectional, 3-sector (120° wide) or 6-sector (3 sectors 120° wide, overlapping with another 3 sectors 120° wide with a different frequency) [52].

Consider the relationship between the parameters in a 6-sector hypothetical network, as shown in Table 4.

NodeB ID	**NodeB Name**	**Sector ID**	**Cell ID**	**UARFCN**	**P-SC**
n_1	Location A	s_1	c_1	u_1	p_1
n_1	Location A	s_1	c_1	u_2	p_1
n_1	Location A	s_2	c_2	u_1	p_2
n_1	Location A	s_2	c_2	u_2	p_2
n_1	Location A	s_3	c_3	u_1	p_3
n_1	Location A	s_3	c_3	u_2	p_3

Table 4: Relationship between the engineering parameters in a 6-sector hypothetical network

The channels are spread using Scrambling Codes, thus creating a differentiation between each sector. The P-SC (Primary Scrambling Code) is specific to the cell, while the S-SC (Secondary Scrambling Code) are used by the MS when actively communicating with the cell [54]. Thus a Node B can serve more than one cell, or sector, as can be seen from Table 4 above. A Node B can transmit at more than one frequency, while the scrambling code identifies the sector. The UARFCN together with the Scrambling Code can thus identify the Node B sector.

The UARFCN indicates the UMTS carrier frequencies and is calculated as follows:

UARFCN = 5 x (frequency in MHz) [55].

For a UMTS network, the signal strengths are measured on the Common Pilot Channel. The RSS gives indication of signal strength in GSM networks and is measured in dBm. RSCP on the other hand, gives an indication of the signal strength in UMTS networks and is not measured in dBm [54].

The field test device failed to measure the Timing Advance (TA) parameter during the drive tests. Furthermore, in GSM networks, TA parameters are only roughly estimated with corresponding distance steps of about 550 meters. Thus, TA has not been included in the methods.

A database was constructed in MATLAB, which consists of data of the fingerprints as shown in Figure 17 below. Each fingerprint corresponds to a certain location. A similar database is constructed for the samples.

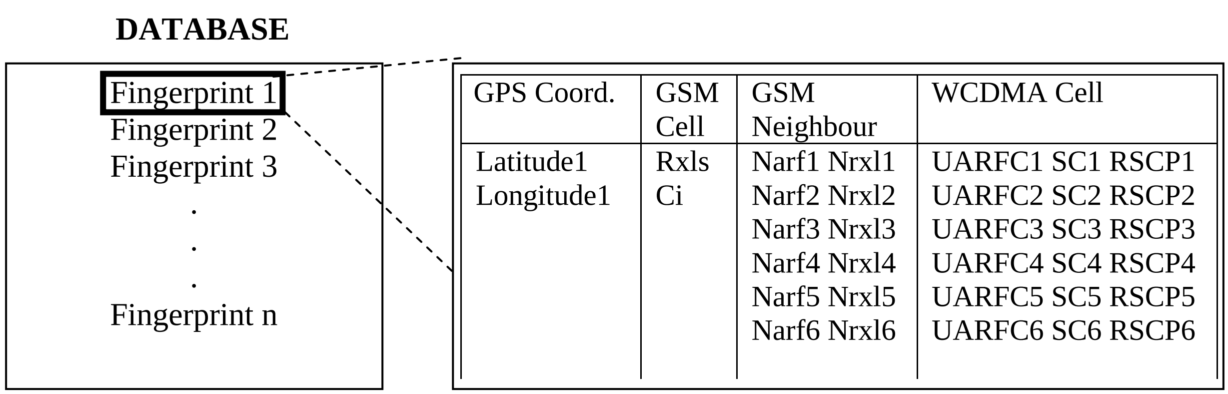

Figure 17: The structure of the fingerprints in the database

3.4. Techniques Using the Strongest Cell

3.4.1. Strongest Cell Approach

For the first approach, only the signal strength from the strongest GSM or WCDMA cell of the database elements, g, as well as that of the samples, f, are considered. Only those *N* elements in g that have common CI's with f are used to form the cost function, $d(k)$. This approach is based on the Least Mean Squares approach taken by Kemppi [18] described in section 2.1.6.3, but only considers the serving cells in the calculations. This basic approach was carried out first to obtain an understanding of the impact of the signal strengths obtained from the strongest cell in the measurements on the cost function used for correlation.

For each sample s, the distance matrix is calculated as follows:

$$d(k) = \sum_{k=1}^{N} (f - g)^2 \qquad \text{...... (24)}$$

The minimum value of the cost function then indicates the best matched fingerprint for each sample. If f does not appear in g, then the second strongest element of the database is considered to form the cost function. For example, consider Figures 18 and 19 below. For a sample fingerprint in the GSM network, this corresponds to $Rxls_{s1}$ and Ci_{s1} from the GSM Cell category. Thus for each fingerprint in the database, an inspection is made to determine whether Ci_{fn} corresponds to Ci_{s1}. If there is no match between these serving CI's, then it is checked if Ci_{fn} corresponds to the second strongest CI detected, $Narf1_{fn}$. The difference between $Rxls_{s1}$ and the corresponding database CI's signal strength can now be found.

GPS Coord.	GSM Cell	GSM Neighbour	WCDMA Cell
$Latitude_{fn}$ $Longitude_{fn}$	$Rxls_{fn}$ Ci_{fn}	$Narf1_{fn}$ $Nrxl1_{fn}$ $Narf2_{fn}$ $Nrxl2_{fn}$ $Narf3_{fn}$ $Nrxl3_{fn}$ $Narf4_{fn}$ $Nrxl4_{fn}$ $Narf5_{fn}$ $Nrxl5_{fn}$ $Narf6_{fn}$ $Nrxl6_{fn}$	$UARFC1_{fn}$ $SC1_{fn}$ $RSCP1_{fn}$ $UARFC2_{fn}$ $SC2_{fn}$ $RSCP2_{fn}$ $UARFC3_{fn}$ $SC3_{fv}$ $RSCP3_{fn}$ $UARFC4_{fn}$ $SC4_{fn}$ $RSCP4_{fn}$ $UARFC5_{fn}$ $SC5_{fn}$ $RSCP5_{fn}$ $UARFC6_{fn}$ $SC6_{fn}$ $RSCP6_{fn}$

Figure 18: Example of a database fingerprint structure for a GSM network

GPS Coord.	GSM Cell	GSM Neighbour	WCDMA Cell
$Latitude_{s1}$ $Longitude_{s1}$	$Rxls_{s1}$ Ci_{s1}	$Narf1_{s1}$ $Nrxl1_{s1}$ $Narf2_{s1}$ $Nrxl2_{s1}$ $Narf3_{s1}$ $Nrxl3_{s1}$ $Narf4_{s1}$ $Nrxl4_{s1}$ $Narf5_{s1}$ $Nrxl5_{s1}$ $Narf6_{s1}$ $Nrxl6_{s1}$	$UARFC1_{s1}$ $SC1_{s1}$ $RSCP1_{s1}$ $UARFC2_{s1}$ $SC2_{s1}$ $RSCP2_{s1}$ $UARFC3_{s1}$ $SC3_{s1}$ $RSCP3_{s1}$ $UARFC4_{s1}$ $SC4_{s1}$ $RSCP4_{s1}$ $UARFC5_{s1}$ $SC5_{s1}$ $RSCP5_{s1}$ $UARFC6_{s1}$ $SC6_{s1}$ $RSCP6_{s1}$

Figure 19: Example of a sample fingerprint structure for a GSM network

3.4.2. Clustering Approach

The basic Strongest Cell approach is modified and used in this approach to determine how effective clustering is. This technique is similar to the previously mentioned approach, with the exception that the K-means method, as introduced in section 2.1.6.3, is used to cluster all the database fingerprints with the same serving CI or second strongest CI as the serving CI of the sample. This is illustrated in Figure 20 on the following page. These multiple location estimates for a sample occur where there is more than one value of k producing a minimum $d(k)$. The number of clusters is found by rounding $M/2$ to the next integer that is lower than or equal to it, where M corresponds to the total number of estimates made for each sample. For example in Figures 18 and 19, all the fingerprints that have Ci_{fn} or $Narf1_{fn}$ in common with Ci_{s1} are clustered for a GSM network. If 10 possible location estimates are made using (24) for a particular sample, a total number of 5 clusters are formed. The kNN classification method, which is described in section 2.1.6.5, is then used on the signal strengths to determine which cluster the sample belongs to. The mean of the GPS coordinates in this group is then used to locate the centre point of this cluster, which defines the estimated location.

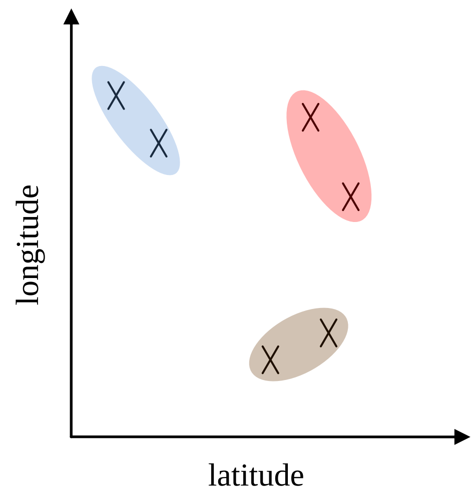

Figure 18: Grouping of d(k) into 3 clusters, where M = 6

3.5. Techniques Using All Detected Cells

3.5.1. Common CI's

The first approach carried out is referred to as the Common CI Approach in this research and is similar to the PCM method introduced by Borkowski *et al* [34] as described in section 2.1.6.3 and is based on the Least Means Square method. This is a basic approach taken to determine how the addition of information on signal strengths obtained from neighbouring BS's of the fingerprint that are common with neighbouring BS's of the sample, influences the accuracies obtained by using the signal strength from the strongest cell alone. This provides a crucial overview of the importance of additional information on signal strengths to form the fingerprints. The cost function is only based on the signal strengths of those CI's that are common between the sample and database fingerprints. Using Figure 21 as an example, these common CI's would be CI's A, B and C. This cost function is calculated using the following equation:

$$d(k) = \sum_i (f_i - g_i(k))^2 \qquad \ldots\ldots (25)$$

In (25), f_i represents the signal strength of the i^{th} CI in the sample that also occurs in the database and $g_i(k)$ represents the signal strength of the i^{th} detected CI in the k^{th} database fingerprint which is also present in the sample.

3.5.2. Inclusion of the Penalty Term

This technique is an advancement to the Common CI's approach, where those CI's that are not in common between the database and sample fingerprints are penalized. This is necessary to determine the relationship between common and uncommon CI's that occur between the database and sample fingerprints, and thus its impact on the results. The Least Mean Squares approach taken by Kemppi [18] in Section 2.1.6.3 was attempted, and then adapted to determine the location estimates.

Consider the example of a database fingerprint and sample as shown in Figure 21.

DATABASE FINGERPRINT	
CELL ID	**RSS (dBm)**
CELL ID A	-83
CELL ID B	-84
CELL ID C	-89
CELL ID D	-99
CELL ID E	-102

SAMPLE FINGERPRINT	
CELL ID	**RSS (dBm)**
CELL ID A	-84
CELL ID B	-86
CELL ID C	-93
CELL ID F	-96
CELL ID G	-99
CELL ID H	-104

Figure 19: An example of the CI's and signal strengths in a database and sample fingerprint

The technique implemented by Kemppi [18] involves the inclusion of all the Cell ID's A to H in the calculation. However, Cell ID's D and E only occur in the fingerprint, while Cell ID's F, G and H only occur in the sample. A very small value is assumed for the RSS of Cell ID's F, G and H in the database fingerprint, assuming that this base station is located far away from the fingerprint. Similarly, this very small value, or threshold, is used for Cell ID's D and E, which do not occur in the sample.

Thus as mentioned in section 2.1.6.3, the difference can be calculated as follows

$$d(k) = \sum_i (f_i - g_i(k))^2 + \sum_j (f_j - Q)^2 + \sum_m (Q - g_m(k))^2 \qquad \text{...... (26)}$$

In (26), f_i and $g_i(k)$are as described for (25) while $d(k)$ is the criteria calculated, representing the difference between the sample and the k^{th} database fingerprint. The signal strength of the j^{th} detected CI in the sample which is not present in the k^{th} database fingerprint is represented by f_j. The signal strength of the m^{th} CI from the k^{th} database fingerprint, which is not present in the sample is represented by $g_m(k)$. A threshold value for signal strength is given by Q and is used where the specific CI is not present in either the sample or the database.

The error, as well as the number of estimated locations per sample, was analyzed for varying values of Q to determine the optimal value of Q. The technique mentioned above is referred to as Dual Penalty Term Approach in this research.

This technique was adapted to exclude the CI's in the fingerprint that do not occur in the sample. The difference is then calculated using the following equation:

$$d(k) = \sum_i (f_i - g_i(k))^2 + \sum_j (f_j - Q)^2 \qquad \text{...... (27)}$$

This second technique is referred to as the Single Penalty Term Approach in this research.

3.5.3. Inclusion of Weights

The influence of weights on the Penalty Term Approaches mentioned in section 3.5.2 is tested. The inclusion of weights is an effort to improve the penalty term approaches by adding further means of discriminating the database fingerprints. The number of common CI's (CI's in the sample that appear in the database fingerprint) should be given more importance in the calculations. Thus a weight is calculated in this approach, which corresponds to the ratio of the number of common CI's, to the total number of CI's detected in the sample.

The weight is calculated using the following equation:

$$w_k = \frac{n_o}{n_s} \qquad \text{......(28)}$$

where n_o is the number of CI's in the sample that appears in the database fingerprint k, and n_s is the total number of CI's that is present in the sample. This weight is then multiplied with (26) and (27). The smallest value of the cost function corresponds to the fingerprint with the closest estimation.

3.5.4. Multiple Weights Approach

The method used by Khalaf-Allah [28] was introduced in section 2.1.6.3 and has been adapted in this approach. This approach further differentiates the database fingerprints, in comparison to the use of weights in section 3.5.3 by including further criteria. These criteria include for example a positive effect on the cost function if the strongest CI's of the database and sample fingerprints are the same. It calculates a weight $w^{(i)}$, where

$$w^{(i)} = w^{(i)}{}_{MM} + w^{(i)}{}_{ND} + w^{(i)}{}_{SN} \qquad \text{...... (29)}$$

$w^{(i)}{}_{MM}$, $w^{(i)}{}_{ND}$ and $w^{(i)}{}_{SN}$ represent the measurement model, neighbourhood degree and strongest neighbour weights respectively. The measurement model weight is represented by equation 30 below:

$$w^{(i)}{}_{MM} = \prod_{j=1}^{M} \frac{1}{\sigma_{RxLev}\sqrt{2\pi}} e^{\frac{-(RxLev_S{}^{(j)} - RxLev_{DB_j})^2}{2\sigma_{RxLev}{}^2}} . \prod_{k=1}^{N} \frac{1}{\sigma_{RxLev}\sqrt{2\pi}} e^{\frac{-(RxLev_S{}^{(k)} - Q)^2}{2\sigma_{RxLev}{}^2}} . \qquad \text{... (30)}$$

In (30), M refers to the total number of CI's detected in the sample. The number of CI's in the sample, which is not detected in the fingerprint, is represented by N. As in the previous section, Q represents a threshold. The standard deviation of the detected signal strengths in the sample is given by σ_{RxLev}. The signal strength of the j^{th} CI in the sample is represented by ${RxLev_s}^{(j)}$, while $RxLev_{DB_j}$ is the signal strength in the database fingerprint of the j^{th} CI which was detected in the sample.

The neighbourhood degree weight is given by the following equation:

$$w^{(i)}{}_{ND} = l \qquad \text{...... (31)}$$

where l is the number of CI's in the sample, that occurs in the fingerprint too.

The strongest neighbour weight is given by the equation given below:

$$w^{(i)}{}_{SN} = \sigma_{SN} \text{ .... (32)}$$

where σ_{SN} equals 1 if the strongest CI in the sample corresponds to the strongest or second strongest CI in the fingerprint. If this is not the case, then $\sigma_{SN} = 0$.

3.5.5. Exponential

The approach taken by Zimmermann [38] as described in section 2.1.6.3 is carried out to evaluate the influence of an exponential cost function. This approach is tested as a variant to the Least Means Square method used in sections 3.5.1 to 3.5.4. This exponential function allows for more importance to be given to small differences than to large differences between the sample and database fingerprints.

The cost function for those cell IDs in the database fingerprint that occur in the sample is given by means of the following equation:

$$P_{common} = \sqrt[n^*]{\prod_{i \in N^*} e^{-\left(\frac{f_i - g_i}{\sigma}\right)^2}} \qquad \text{......(33)}$$

The number of common CI's is represented by n^* in (33). The signal strength of the i^{th} detected CI in the sample is represented by f_i, while g_i represents the signal strength of the i^{th} detected CI in the database, which is also present in the sample.

Those CI's that are not common in both the database and sample fingerprints, are penalized as follows

$$P_{Pen} = \sqrt[n']{\prod_{i \in N^*} e^{-\left(\frac{g_i - m_{min}}{\sigma}\right)^2}} \qquad \ldots\ldots(34)$$

In (34), n' represents the number of CI's that are not common between the sample and database fingerprints, whereas m_{min} represents the lowest signal strength in the sample fingerprint.

The final penalty term is then calculated as follows:

$$P = \sqrt{P_{common} \, . P_{Pen}} \qquad \ldots\ldots(35)$$

3.5. Map matching

The GPS device estimates the location of a user with only a certain degree of accuracy. For this reason, the errors in the locations measured using the GPS device need to be reduced using the map matching technique. To create a digital map of the paths taken, Google Maps [48, 61] was used to determine the exact GPS coordinates along the roads where the measurements were taken. Let (sx_i, sy_i) refer to the coordinates obtained from Google Maps [48, 61] and (mx_j, my_j) refer to the measured GPS coordinates used in the database. Thus $d(j)$, the closest actual digital coordinates to the measured coordinates, is calculated by using the following equation:

$$d(j) = minimum\left(\sqrt{(mx_j - sx_i)^2 + (my_j - sy_i)^2}\right) \ \ldots\ldots\ldots (36)$$

3.6. Summary

The various techniques mentioned in this chapter were aimed at improving the precision of the pattern matching method for a developing country. These techniques were chosen and modified, such that an effective comparison can be obtained between them. The possible variables that could affect the positioning algorithms had to be kept constant. These variables included environment, time of day, weather and type of device used for measurements. Thus, the field tests carried out to form the database and samples were limited to suburban environments and only the geographical location was changed. The suburban areas that were chosen had differing levels of dominance of either WCDMA or GSM networks. The Radio Frequency signal measurements that were obtained during the field tests were used together with the measured GPS coordinates to construct a database of fingerprints.

Chapter 4 will provide a detailed analysis of the results obtained by implementing these various techniques in two suburban environments. The level of importance which should be given to those CI's that are common between the sample and database fingerprints was studied. The influence of clustering, the use of weights as well as the performance of the techniques in the GSM and WCDMA networks have been analyzed and are presented in Chapter 4.

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4. Results and Analysis

4.1. Introduction

The techniques mentioned in chapter 3 were tested in two suburban areas in South Africa. Area A refers to the suburb of Lynnwood in Pretoria, while Area B refers to the suburb of SE 1 in Vanderbijlpark. The characteristics of the areas, in terms of the availability of the various measurement parameters that were captured in a GSM and WCDMA network are described in this chapter. The results obtained from varying values of the penalty term in (26) and (27), as well as the relationship between the weights described in (28), the penalty term and the accuracy that it produces is also analyzed. The results obtained from testing the various techniques are then displayed and analyzed.

4.2. Area A

4.2.1. General

From the field tests that were performed, 331 fingerprint measurements were obtained for the database, while 41 measurements were taken for the samples, which will be used to test the techniques presented. Up to 6 WCDMA CI's (including the serving cell and 5 neighbouring cells) were detected per fingerprint location. In the GSM network, a maximum of 7 GSM CI's (including the serving cell and 6 GSM neighbouring cells) were measured per fingerprint. As was noted in chapter 3, the Lynnwood area had predominantly WCDMA coverage.

4.2.2. Measurement Data

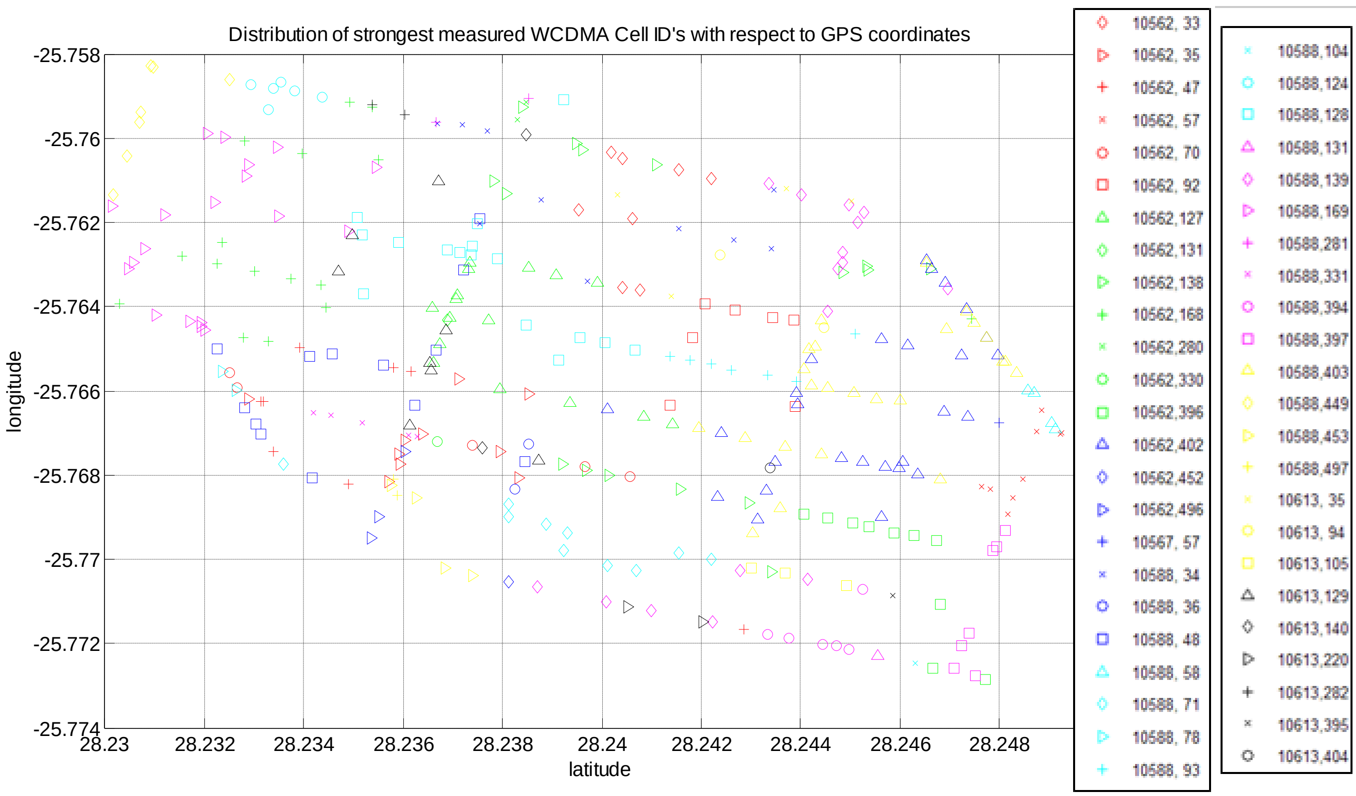

Figure 20: Distribution of strongest measured neighbouring WCDMA Base Stations with respect to GPS coordinates

Figure 22 represents the distribution of the serving WCDMA cells with respect to location. A total of 52 different WCDMA CI's were detected as the serving CI amongst the database fingerprints, as can be seen from Figure 22 above. However, 98 CI's were picked up altogether amongst all the WCDMA CI's in the database. The first number in the legend indicates the UMTS Absolute Radio Frequency Channel Number, while the second number represents the Scrambling Code. Figure 22 shows that the serving CI's vary quite a lot as one moves from one location point to the other. Thus it appears that the serving CI has potential of giving a relatively good location estimate.

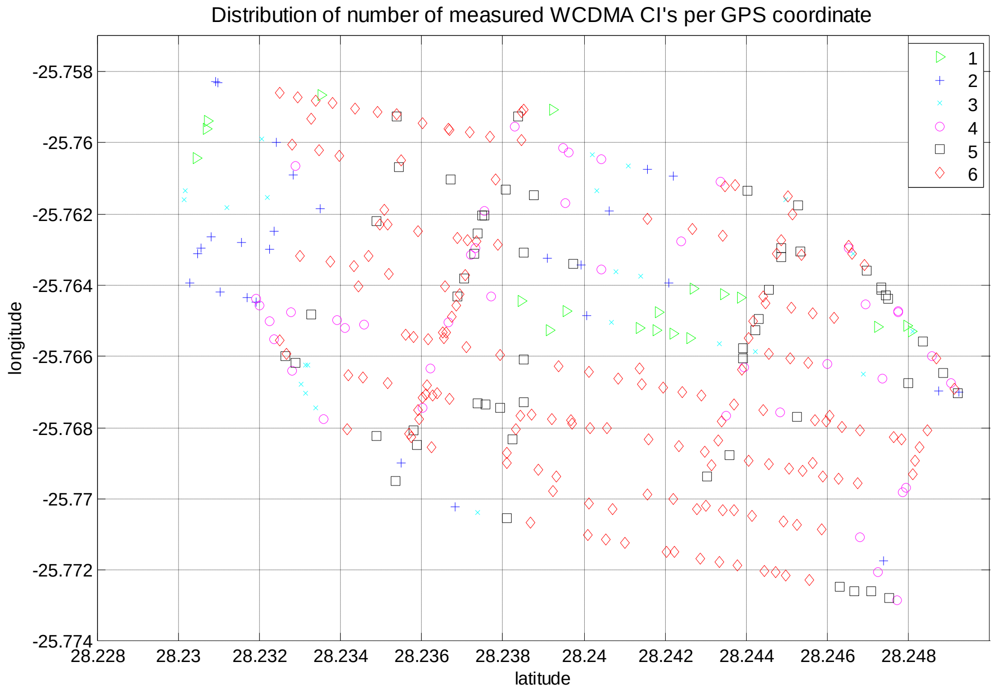

Figure 21: Distribution of the number of measured WCDMA neighbours per GPS coordinate

The WCDMA CI's were detected in all the measurement positions for the database. Although it was expected to ideally obtain measurements of all six WCDMA CI's in each fingerprint, all six WCDMA neighbours were only detected in 49.6% of the fingerprints in the database. However, 79 % of the fingerprints included more than 3 WCDMA neighbours. This is illustrated in Figure 23 and is due to factors such as reflections off trees, buildings and other objects in the environment which block the propagation of the signal. Kemppi [18] describes how the number of hearable cells affects the resolution of the DCM fingerprints. Thus, the fewer the number of hearable cells, the greater is the area where the same signal levels will be measured.

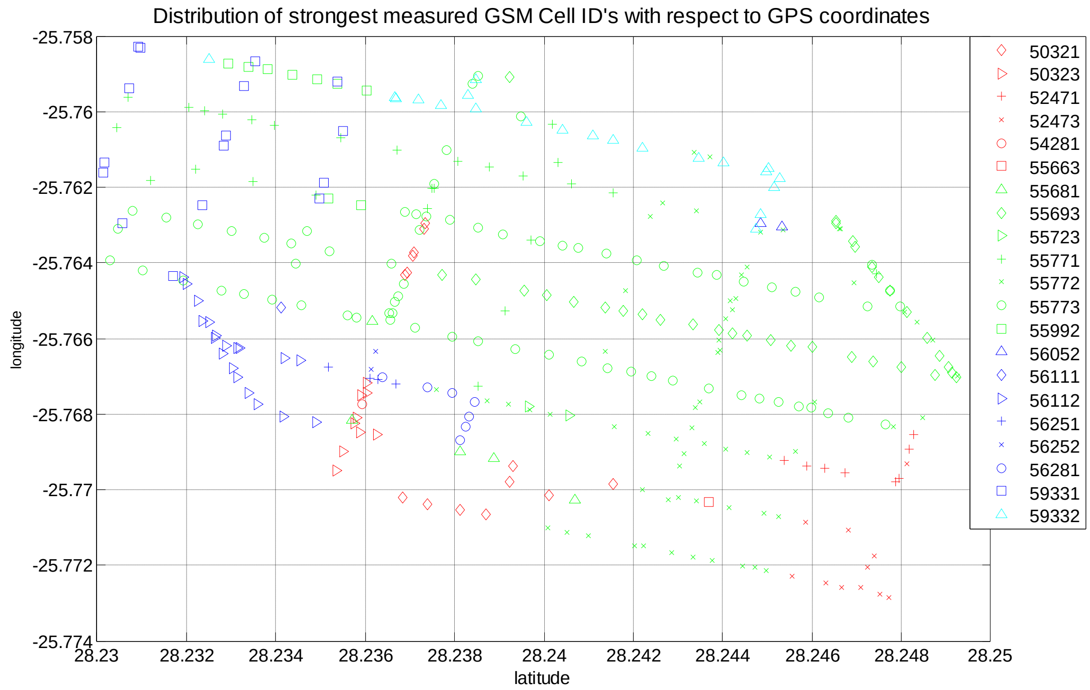

Figure 22: Distribution of strongest measured GSM Cell ID's with respect to GPS coordinates

As can be seen in Figure 24 above, there were 21 different GSM CI's that were detected as the serving cell in the specific area. Even though the GSM neighbours were not detected in the majority of the positions, the strongest GSM Cell was always detected. A total of 27 GSM CI's were detected amongst all the GSM neighbours. In those location points where the GSM neighbours were detected, all 6 of the neighbours were detected. In contrast to the serving WCDMA CI that was measured, the GSM system indicates much larger areas with the same serving CI's. This makes it more difficult to correlate these location points based on serving CI's alone, since one has to rely heavily on the signal strength in these areas where the serving CI's match. This may result in less accurate position estimates since slight fluctuations were observed in the signal strengths.

Figure 25 displayed below, indicates the distribution of the samples in relation to the database fingerprints. The WCDMA neighbours were not detected at all in 7.9% of the cases for the sample. Similar to the GSM database, the GSM neighbours were not detected in the majority of the measurements. It was only detected in 22% of the sample measurements. However, the strongest GSM cell was always detected. Thus it can be concluded from these preliminary observations that the use of GSM neighbours alone is not sufficient enough to distinguish the location points in the correlation procedure in this area with predominantly WCDMA coverage.

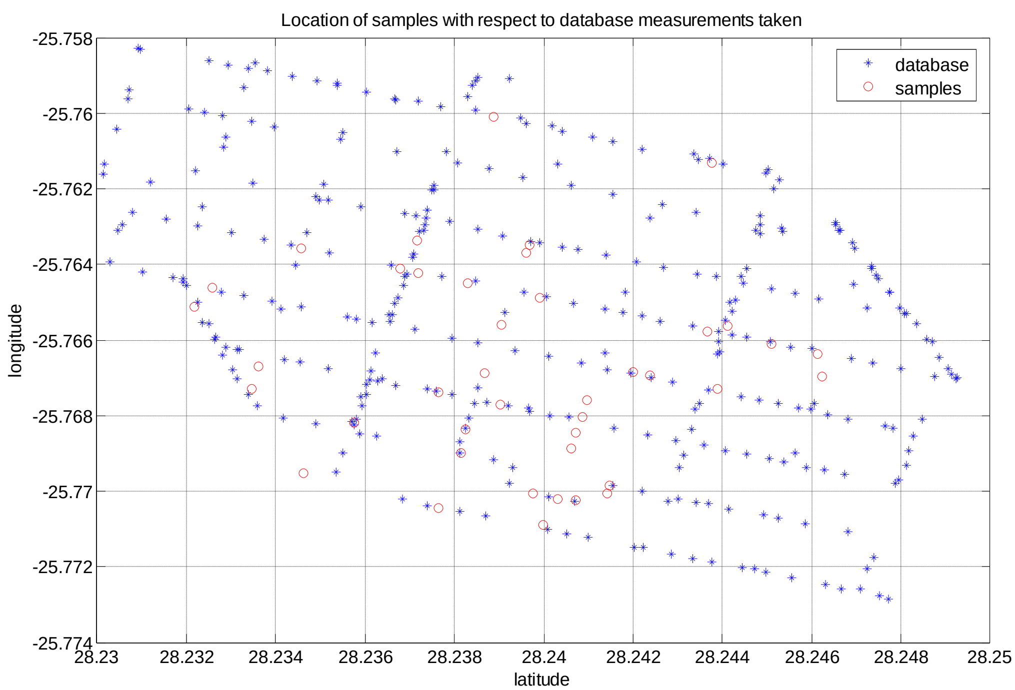

Figure 23: Location of the samples with respect to the database measurements for a WCDMA network

Figure 26 on the following page displays the resultant positions of map matching. Slight improvements can be seen in certain areas.

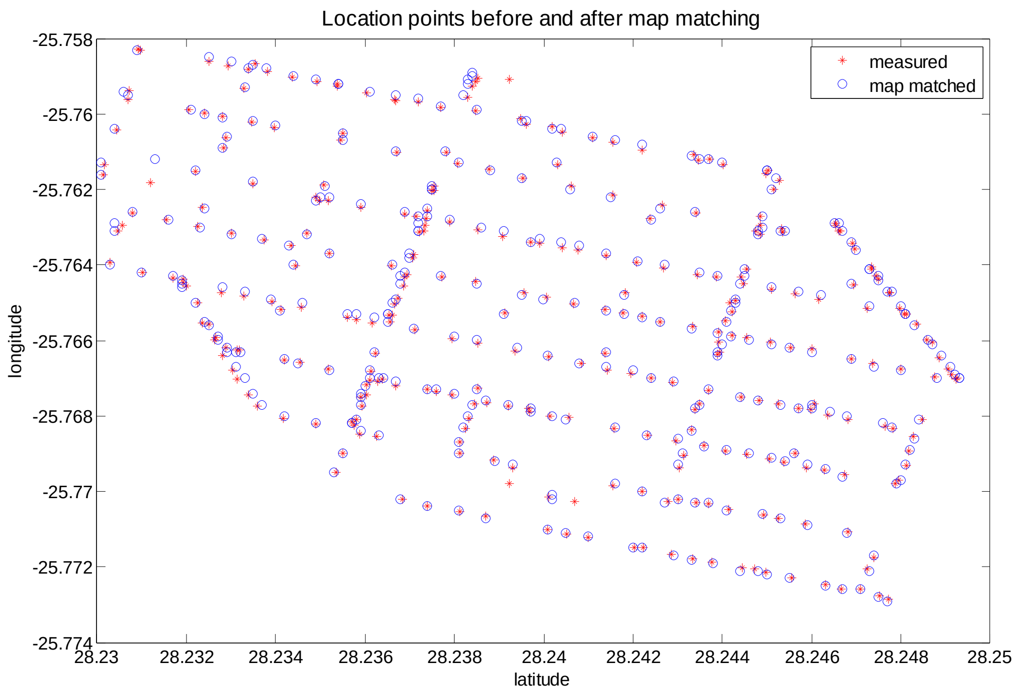

Figure 24: Measured locations vs. map matched locations

4.2.3. Analysis of the Parameters

The value of the penalty term, Q, in (26) and (27) was varied from -250 to 0 and its impact on the accuracy was observed. In addition, the effect of the weight, w_k, described in (28) was also analyzed. As defined in section 3.5.2, the Dual Penalty Term Approach uses penalty terms for the undetected sample and database BS's and is given by (26). The Single Penalty Term Approach only uses a penalty term for the undetected database BS's and is given by (27). These approaches are used with and without the weights, w_k, used in (28) as described in section 3.5.3. Figures 27 to 30 show the relationship between w_k, Q and the accuracy for the Penalty Term Approaches. In those cases where more than one location point was estimated, the mean of the errors for these location points were found and an average number of estimates were recorded for the particular technique. It is expected that for values of Q below the range that was measured for the WCDMA and GSM signal strengths, the number of estimated locations per sample should stabilize to a minimum. Outside this range, Q should have less interference with the existing data.

Since this is an area which has majority WCDMA coverage, the WCDMA network is expected to show a more stable graph than that for the GSM network. The Single Penalty Term Approach is expected to yield better results than the Dual Penalty Term Approach since it does not overemphasize the effect that the CI's that are not common between the database and sample fingerprints, should have on the cost function. The use of weights is also expected to better the results since it increases the discriminative power of the cost function.

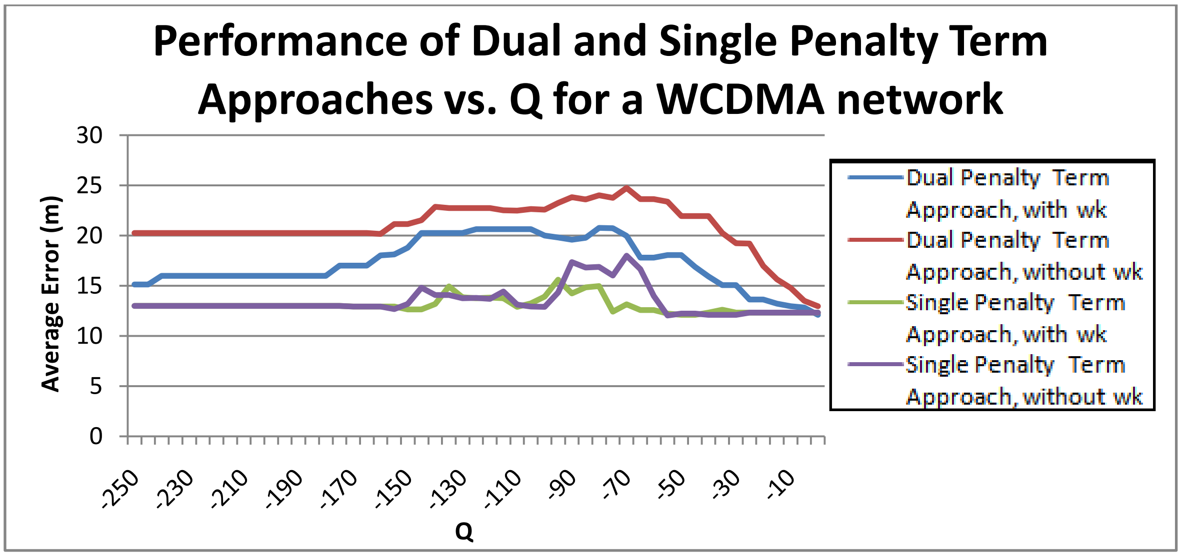

Figure 25: Average Error of Dual and Single Penalty Term Approaches vs. Q for a WCDMA network

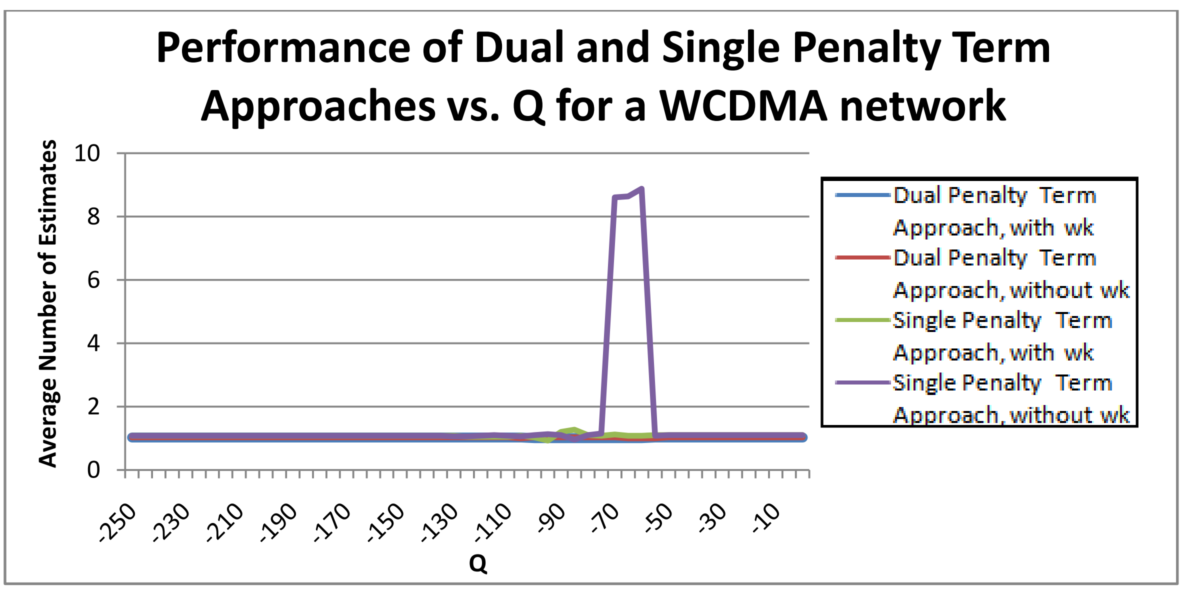

Figure 26: Average number of estimates of Dual and Single Penalty Term Approaches vs. Q for a WCDMA network

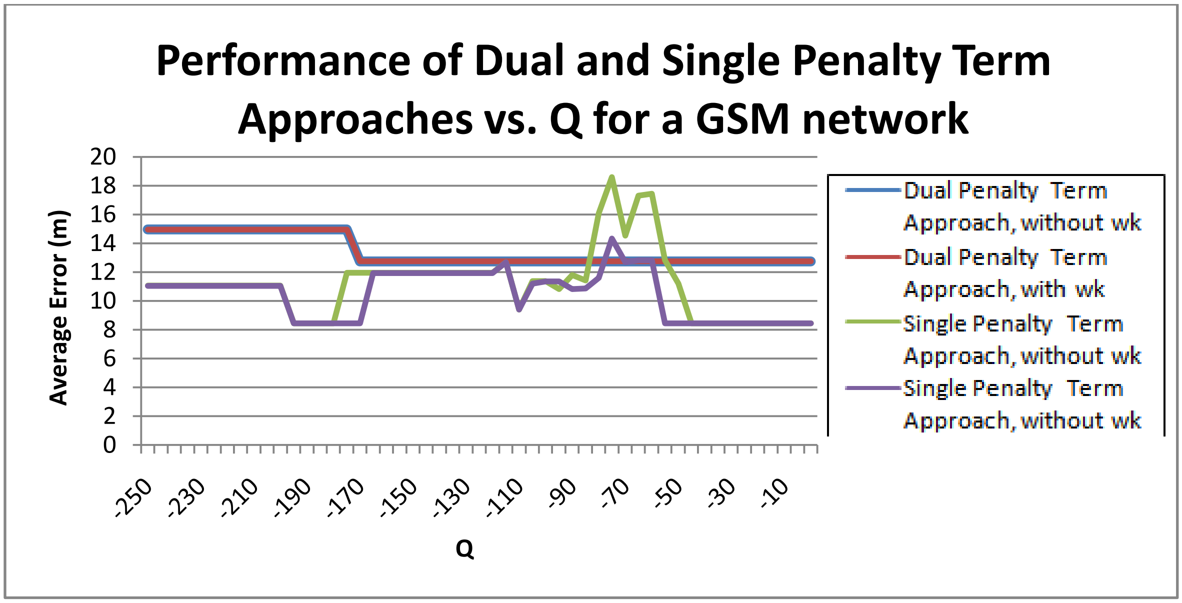

Figure 27: Average error of Dual and Single Penalty Term Approaches vs. Q for a GSM network

It must be noted that the Dual Penalty Term Approach without w_k and the Dual Penalty Term Approach with w_k produced the overlapping graphs in Figure 29 above.

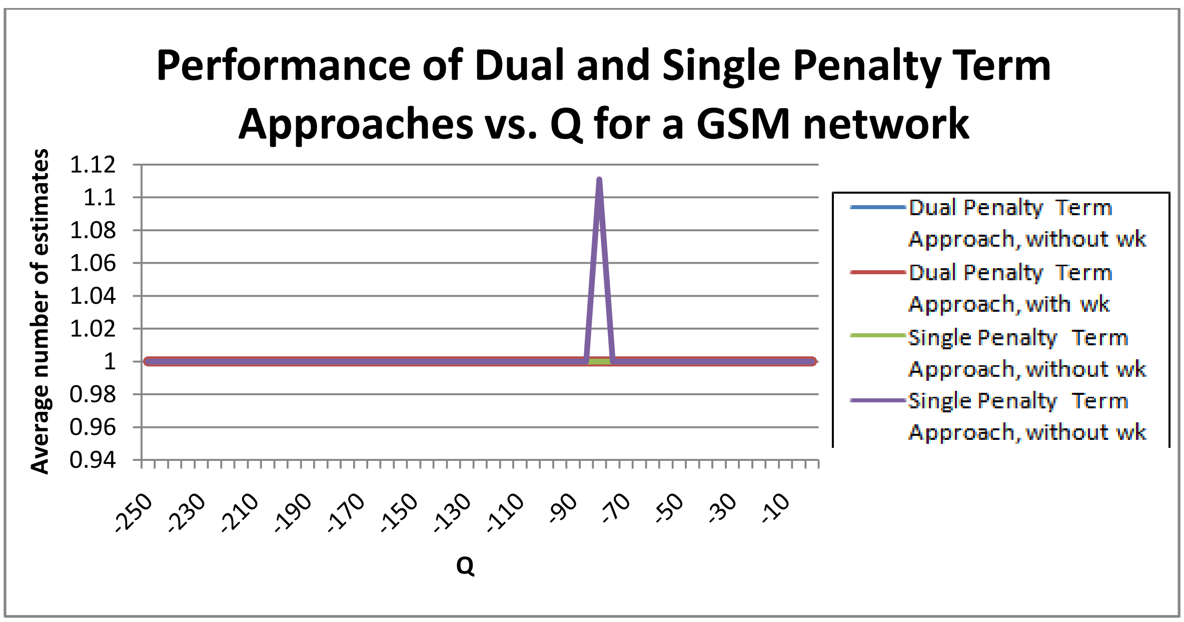

Figure 28: Average number of estimates of Dual and Single Penalty Term Approaches vs. Q for a GSM network

In Figure 30 displayed above, it is to be noted that an average number of estimate of one was obtained for the approaches for the values of Q tested. The only deviation was seen for the Single Penalty Term Approach with w_k where Q is equivalent to -80. Thus the Dual Penalty Term Approach without w_k, the Dual Penalty Term Approach with w_k and the Single Penalty Term Approach without w_k produce overlapping graphs in Figure 30.

From Figures 27 and 28 it is observed that for values of Q below -150 for the Single Penalty Term Approach, the average error of the samples stabilizes. Below this value of Q, w_k no longer has an impact on the accuracy or the number of estimates. Thus as expected, for a value of Q outside the range of measured signal strengths, the Single Penalty Term Approach yields both better levels of accuracies as well as average number of estimates.

In general, the use of weights does increase the discriminative power as expected and better results in terms of both accuracy and average number of estimates is seen. It appears that the use of weights has a greater impact on the Dual Penalty Term Approach than for the Single Penalty Term Approach in a WCDMA network. This is due to the Single Penalty Term Approach having a more stable cost function in terms of finding a balance between the common and uncommon CI's. However, for a value of Q outside the measured range, weights do not seem to have an impact on the average number of estimates.

For the GSM network, in those locations where the GSM neighbours were detected, all 6 CI's were always picked up. However, in the WCDMA network, there were fewer hearable CI's that were detected. For this reason, w_k has a greater impact on the WCDMA network since this network has less discriminating power due to the fewer hearable CI's. This can be seen in Figures 27 and 29, where w_k improves the accuracy of both approaches in the WCDMA network. However, w_k only has an influence on the Single Penalty Term Approach in the GSM network where it reduces the error. Thus on the whole, w_k adds greater influence on the cost function for the correlation.

Figures 29 and 30 indicate that values of Q smaller than -160 appear to yield the best results with respect to errors for the Dual Penalty Term Approach and the Single Penalty Term Approach in the GSM network. In addition, the average number of estimations per sample stays constant for all values of Q outside the measured signal strength range, for the Dual Penalty Term Approach. This is due to the diversity in the database fingerprints and the good discriminative power of the Penalty Term Approaches. In addition, there is a less drastic fluctuation in the accuracy of the WCDMA network for values of Q outside the range.

The lowest average error is obtained for values of Q between -190 and -180 or greater than -50 for the Single Penalty Term Approach. The optimal value for Q appears to be a value between -170 and -130 for the techniques in both the networks, where the error stabilizes at a relatively low value for both techniques used. However, to agree with the logic that those CI's that are not common between the database fingerprint and the sample, are located far away from the fingerprint location and thus have a very low value (as described in section 3.5.2.), a practical value of -160 is chosen for Q.

4.2.4. Techniques Used to Improve the Correlation

Figures 31 to 33 on pages 74 and 75 illustrate the average errors and average number of estimates obtained for the various location points. It must be noted that in some cases, multiple possible location estimates were obtained for a sample. This was particularly noted when a single network was used. In these cases, all the possible estimates were considered, and the mean of their errors were found for that particular sample. Multiple location estimates were further analyzed using data from both networks. In addition, the same number of estimates was obtained with and without map matching and is displayed by Figure 33 on page 75.

It is expected to see the poorest performance for the Strongest Cell technique since the use of the serving cell alone cannot provide enough discriminative power for the correlation. In Area A, the GSM network had larger areas of similar serving CI's, as observed in section 4.2.2. Thus there is less discriminative power than in the WCDMA network and the GSM network is expected to show poorer results for the techniques that only use the data from the serving cell. Clustering is expected to improve these results even though only the strongest cell is used, since it eliminates outliers and it eliminates the problem of multiple estimates. The best results are expected for the Single Penalty Term Approach since it considers both the common and uncommon CI's in the correct proportion for the cost function. On the other hand, the Dual Penalty Term Approach is expected to obtain higher errors than the Single Penalty Term Approach since the cost function gives twice as much importance to the uncommon CI's as to the common CI's. The use of weights is expected to further emphasize the similarities between the sample and database fingerprints. In general, the WCDMA network is expected to show better results than the GSM network since Area A is predominantly WCDMA and should thus display more diverse WCDMA data for the fingerprints. The combined use of both the networks is also expected to improve the results since it also provides additional factors for comparison in the correlation process. The common CI's only technique is not expected to perform well since it only considers the common CI's and those CI's that are not common have not been penalized in this process. However, this technique should help in giving an indication as to how much importance should be given to the common and uncommon CI's in the cost function. The Multiple Weights technique should perform better than the Exponential technique since the use of the detailed weights should help to further differentiate the individual fingerprints. Map matching is expected to improve the results as well since it eliminates any errors in the GPS measurements.

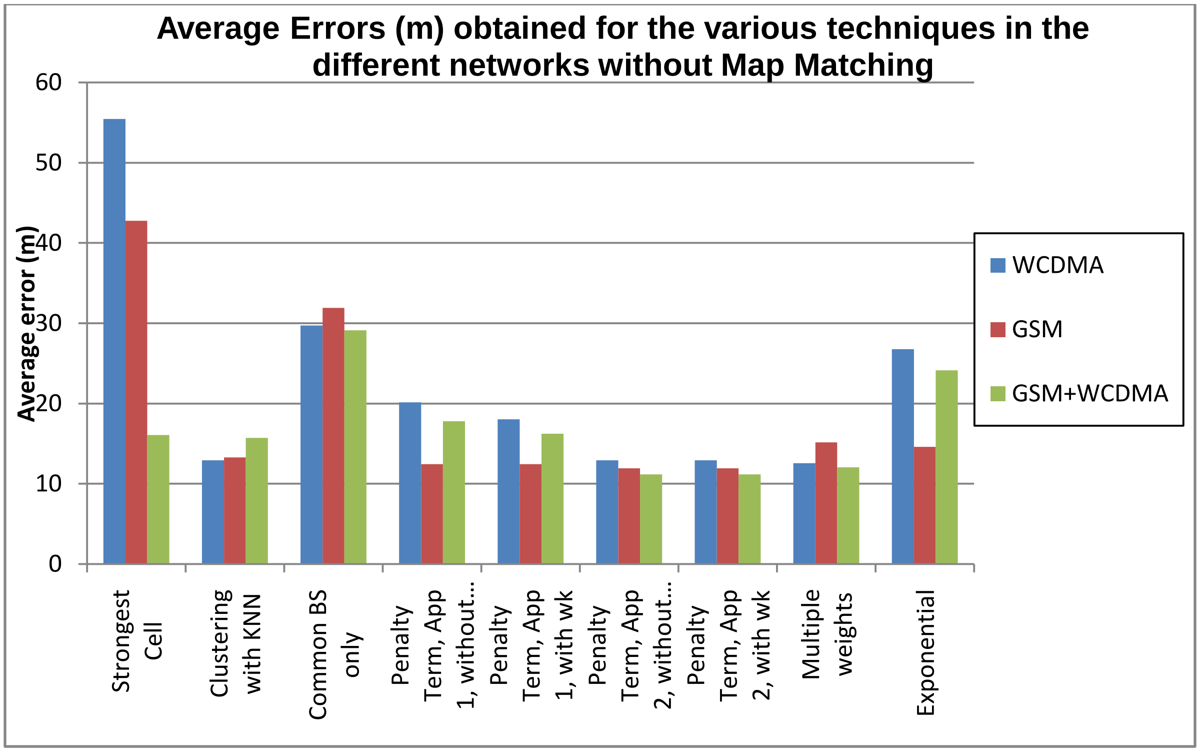

Figure 29: Average errors for the various techniques in the different networks without Map Matching

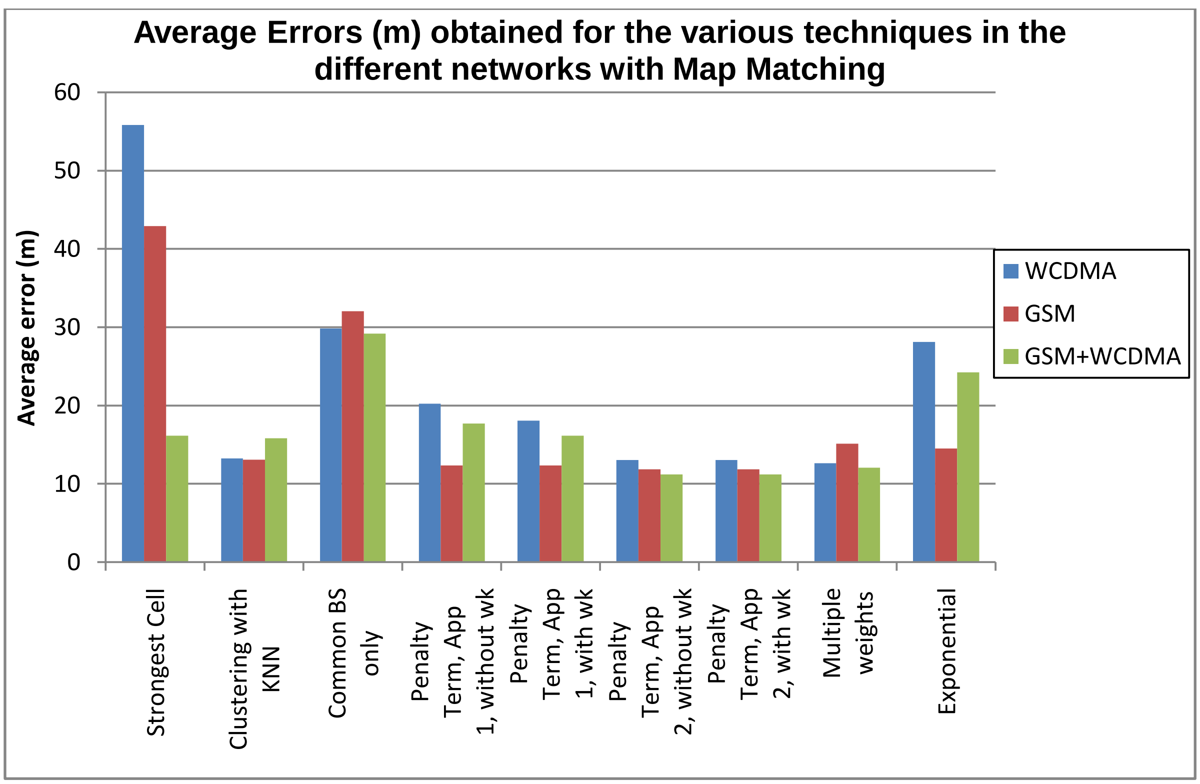

Figure 30: Average errors for the various techniques in the different networks with Map Matching

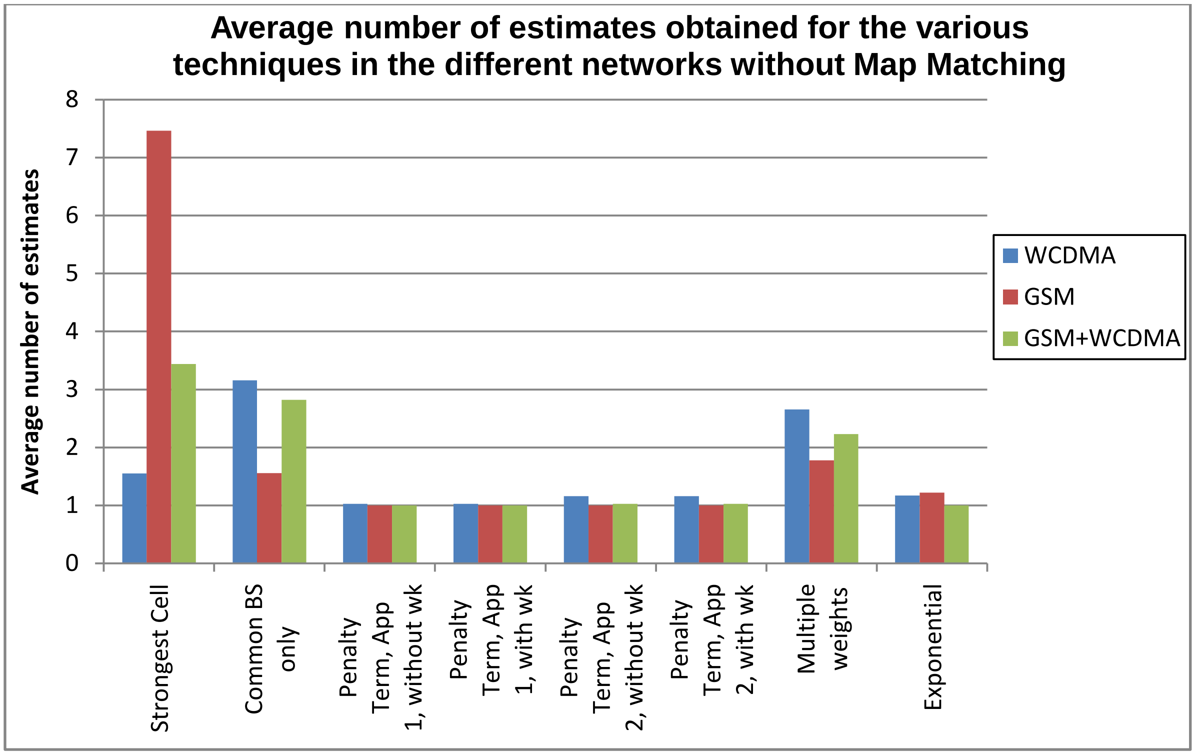

Figure 31: Average number of estimates for the various techniques in the different networks

From the results obtained for the WCDMA and GSM networks in Figures 31 to 33, it was noted that just using the strongest CI alone, without clustering, is not very reliable. In both the networks, the signal strength of the strongest cell cannot be used alone to determine the location estimate due to fluctuations in signal strength. The signal strength of the strongest and second strongest cell may only differ by a slight amount, which may mean that this strongest neighbour is detected in some cases in the same area due to multipath propagation. Thus it is not reliable to use only a single cell measurement to form the database. For instance, in the WCDMA network the average difference between the signal strengths of the serving cell and the strongest neighbour was found to be 3.4565 for the database, while on average the difference between the minimum and maximum detected signal strengths of the 6 WCDMA neighbours was found to be 15.81. Thus it can be seen that the difference in signal strength values of the neighbours is not large enough to give importance to the strongest WCDMA neighbour alone. In addition, the strongest cell's signal strength was constant in certain areas for the GSM network. As a result the average number of estimates for the Strongest Cell technique in a GSM network is very high at a value greater than 7. More importance should be given to the cells that have the same CI as the sample, rather than to the signal strength.

On the other hand, in both the GSM and WCDMA networks, clustering improved the accuracy significantly by eliminating outliers, resulting in the error obtained by clustering being only 23%-31% of that obtained by using the strongest cell alone.

The results indicate that the best method in terms of accuracy as well as the number of estimates, is the use of the Single Penalty Term Approach, where the database CI's that are not common with the sample CI's, are ignored. More importance should thus be given to how much of the sample is matched by the database fingerprint, and not to how much of the fingerprint has been matched by the sample as well. This justifies the omission of these database CI's in the calculations, in comparison to the Dual Penalty Term Approach.

Figure 34 demonstrates how, the addition of the database CI's that do not occur in the sample, results in a decline in the accuracy for a WCDMA network. This is also observed in the GSM network. The Dual Penalty Term Approach includes these abovementioned CI's, while the Single Penalty Term Approach does not. From Figure 33, it appears that the only advantage that the inclusion of these CI's in a WCDMA or GSM network yields is that there is a slight reduction in the multiple estimates of the location for the Dual Penalty Term Approach. This could be as a result of greater discrimination of the fingerprints by the inclusion of these CI's. However, even with a greater discriminative power, there is only a slight decline in the accuracy.

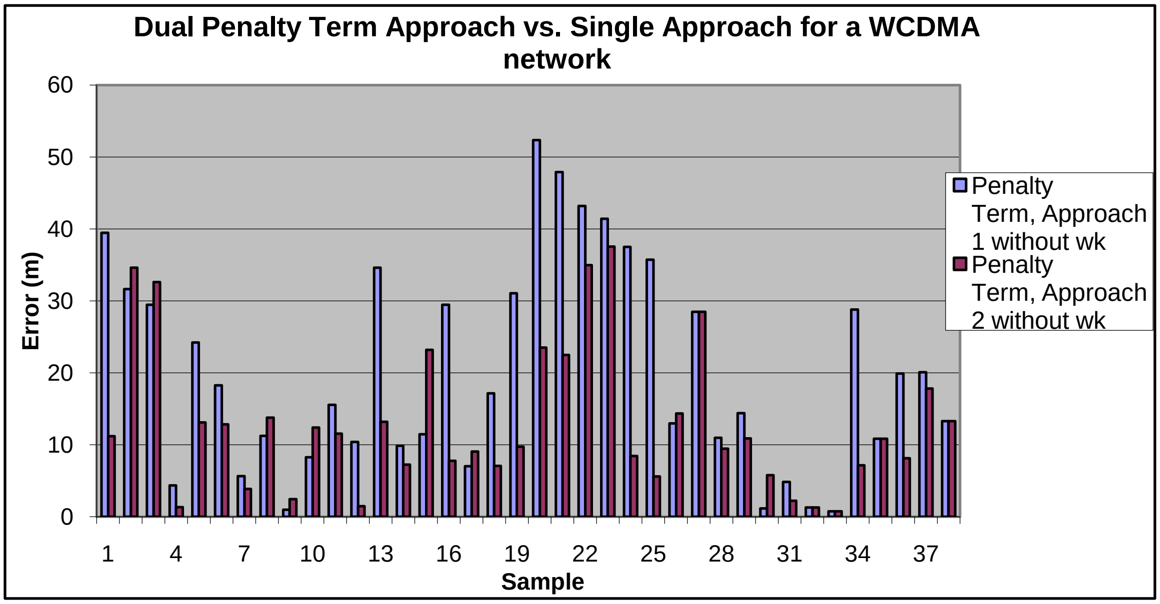

Figure 32: Comparison of Dual and Single Penalty Term Approaches for a WCDMA network

The use of weights only saw an improvement in the accuracy for the Dual Penalty Term Approach in the WCDMA network.

It is not feasible to use GSM measurements alone since it is not detected in the majority of cases. Using a combination of both GSM and WCDMA measurements yielded the best results in the case of Strongest Cell, common CI, Single Penalty Term Approach and Multiple Weights approaches. However, using a combination of the networks also means that both the strengths as well as the flaws of the two network measurements are incorporated.

Map matching did not influence the results in the majority of the cases for the WCDMA and GSM networks combined. From the average errors, only a very slight difference was observed in the results when map matching was used. This difference is too small and is not clearly visible in the Figures 31 and 32. On average, the WCDMA network saw a slight decline in accuracy, while the GSM network saw a very small increase in accuracy.

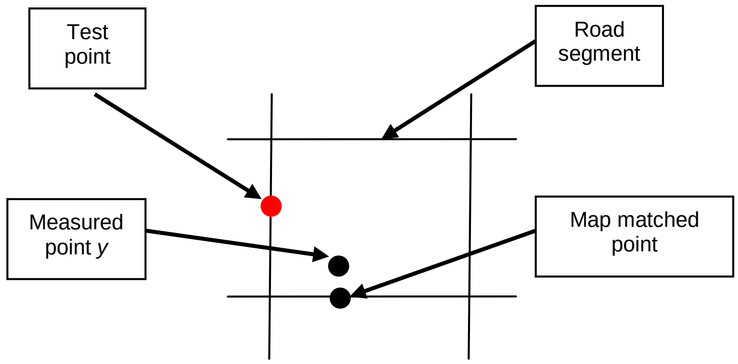

Figure 33: Illustration of the cause of an in increase in error due to map matching

This decline in accuracy is a result of the predicament pointed out in Figure 35 above. The measured point may be correctly matched onto the digital map. However, instead of correlating to a database fingerprint located closer to it on the same road segment, it has correlated to point *y* which is further away. Thus, this slight increase in the error which is seen in the WCDMA network is not a result of incorrect map matching, but rather of errors in the correlation due to the inadequate precision in the cost function of the techniques.

Ideally, one reliable estimate is required. However even after using a combination of WCDMA and GSM data, single estimates are only obtained for the Penalty Term 1 and Exponential approaches.

4.3. Area B

4.3.1. General

A total of 325 fingerprints were created from the field tests to form the database, while 62 sample fingerprints were measured for the tests. Although this area has predominantly GSM coverage, at least one WCDMA CI was detected in most of the location points.

4.3.2. Measurement Data

Figure 36 is a display of the distribution of the number of measured WCDMA neighbours. It illustrates the fact that greater than 3 neighbours were only measured in 30% of the locations, while only 1 neighbour was detected in another 31% of the locations. However, the samples had better hearability of Node B's, with 44% of the test fingerprints containing greater than 3 neighbours.

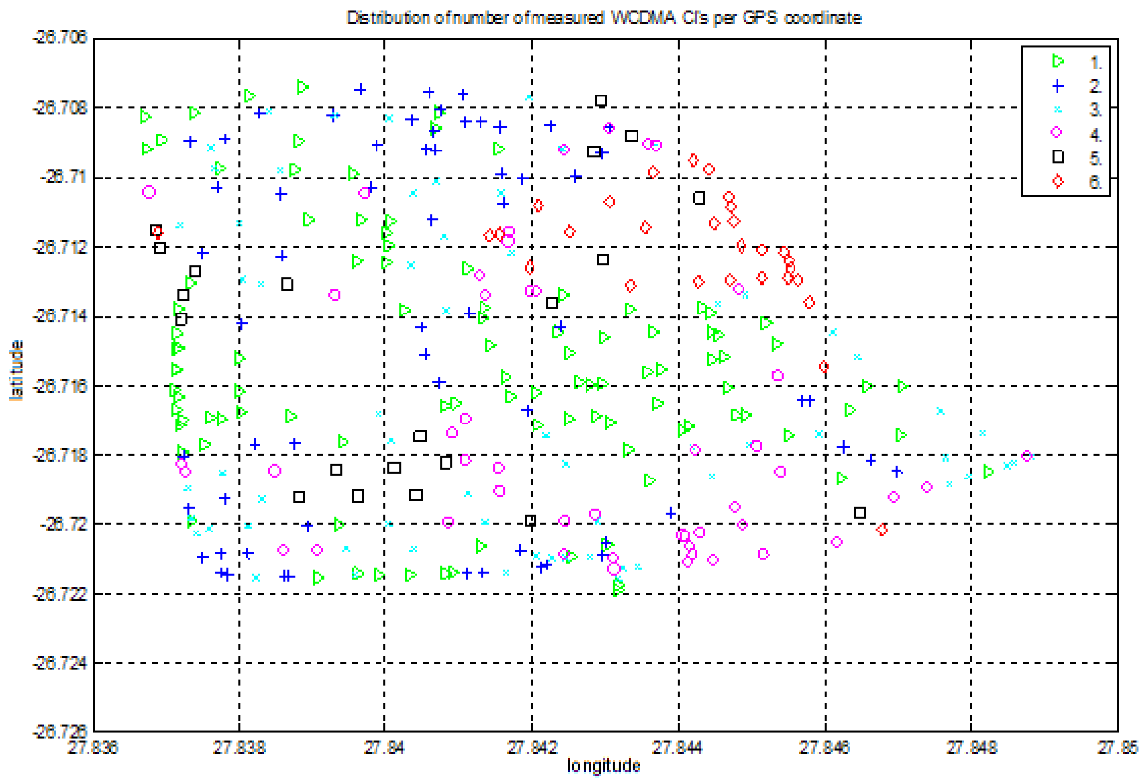

Figure 34: Distribution of the number of measured WCDMA CI's with respect to location

Figure 37 illustrates that 15 CI's were picked up as the serving cells in the area. This is far less than that detected in Area A.

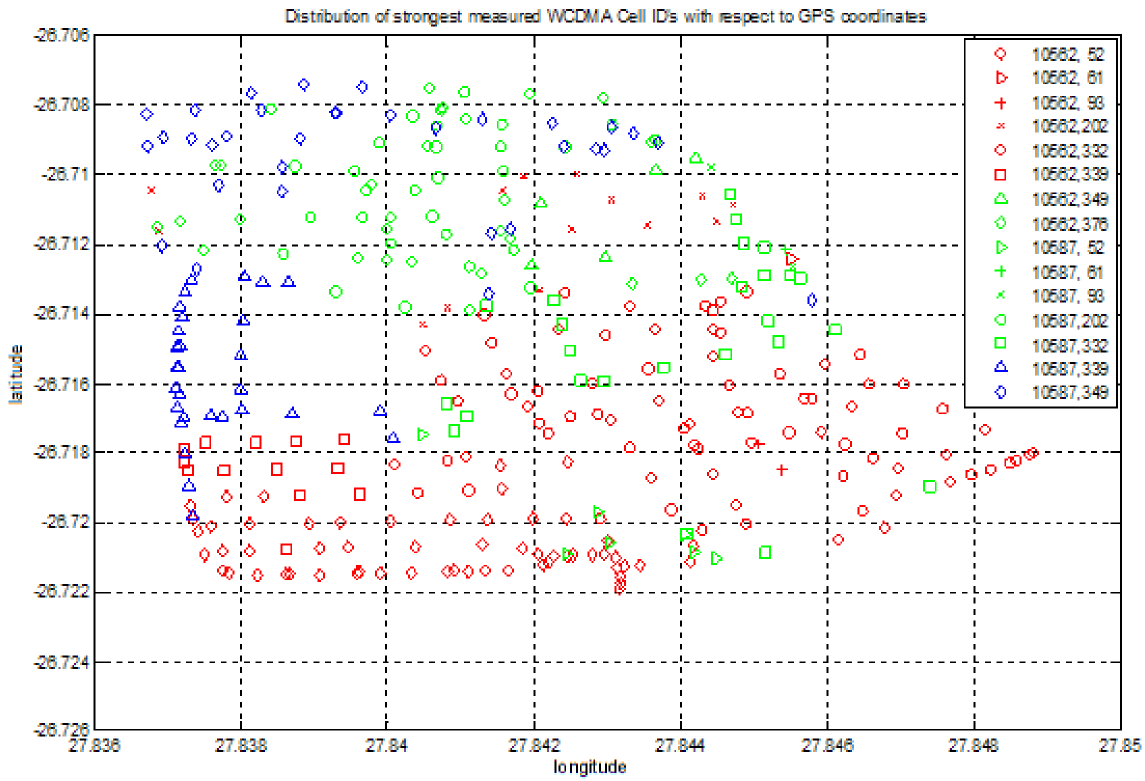

Figure 35: Distribution of the strongest measured WCDMA CI's with respect to GPS coordinates

Figure 38 shows the distribution of the strongest measured GSM CI's. It can be seen that 10 different CI's were picked up as the serving cells. The GSM neighbours were detected in 99% of the locations. In all these locations, all 6 neighbours were picked up in the field tests.

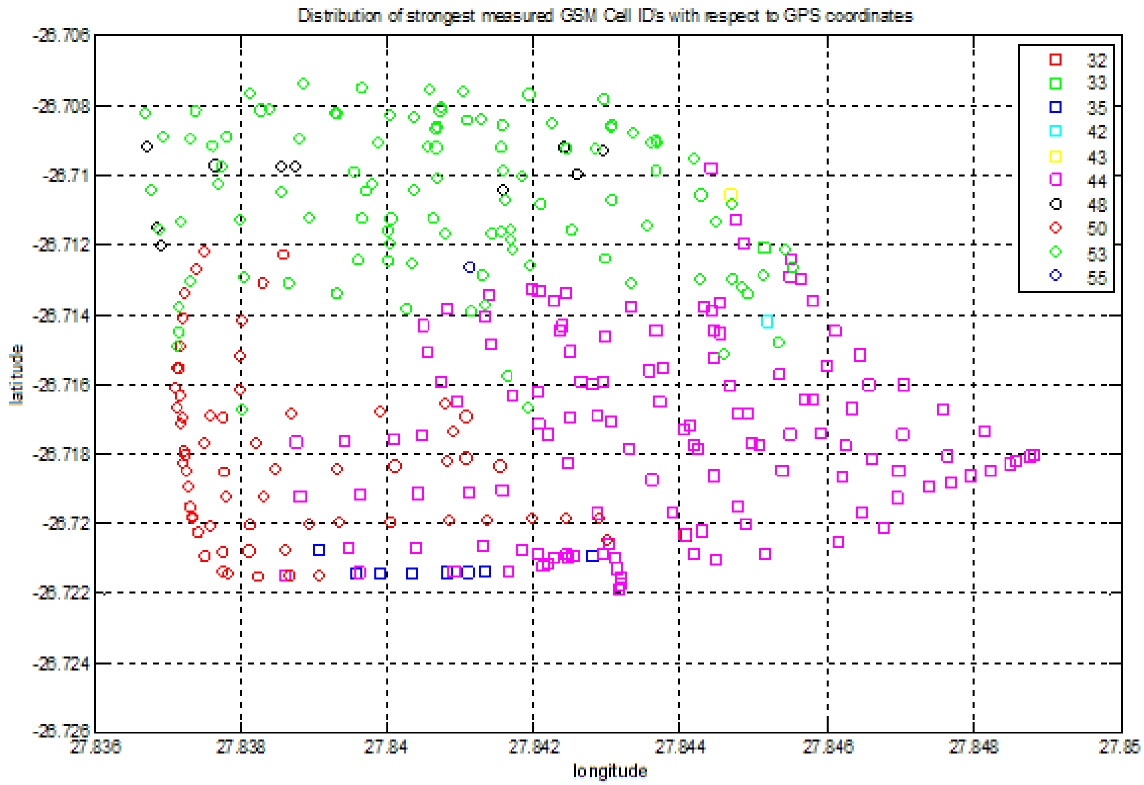

Figure 36: Distribution of the strongest measured GSM CI's with respect to GPS coordinates

Figure 39 illustrates the location of the samples with respect to the database measurements. A separate drive test was taken to obtain the samples.

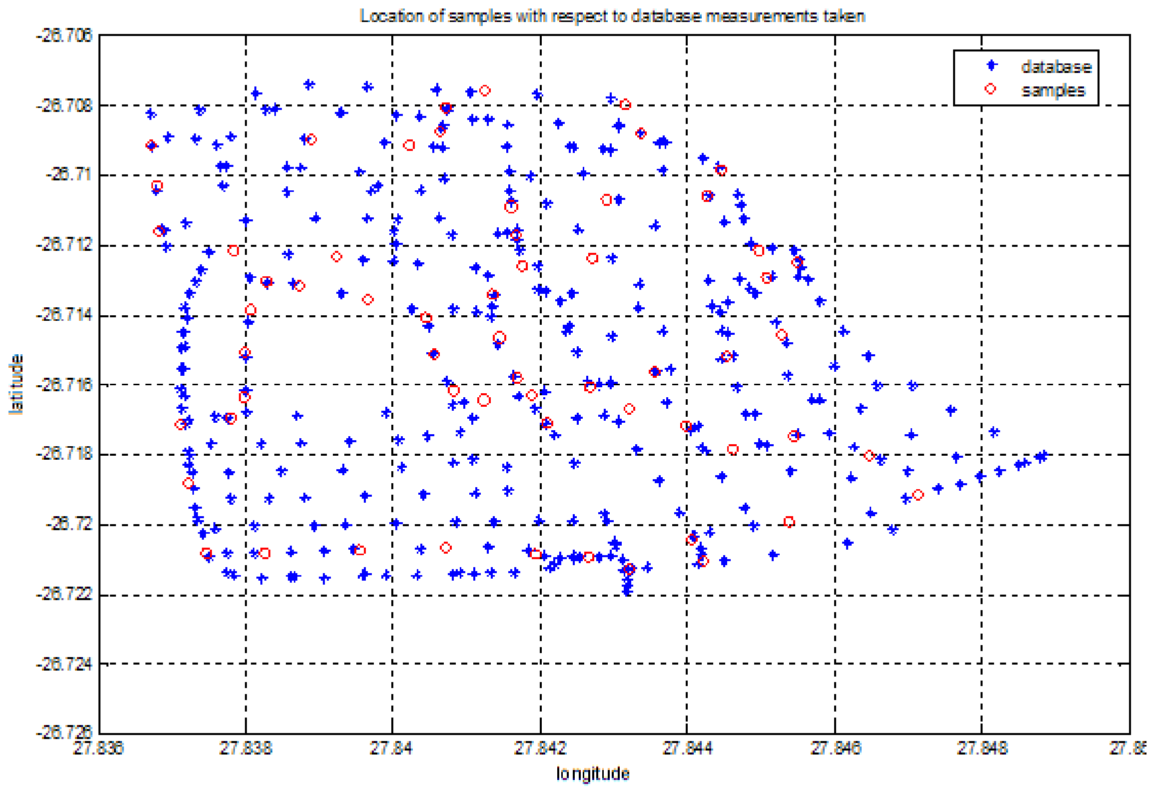

Figure 37: Location of samples with respect to database measurements

4.3.3. Analysis of the Parameters

Figures 40 and 41 indicate the average error obtained for the Penalty Term Approaches for varying values of Q, as in (26) and (27), in a GSM network and WCDMA network respectively. As in the case of Area A, a very small value for Q can be expected to yield the best results, if it is assumed that this undetected BS is located at a distance far away. A realistically sized value should be assumed for this undetected BS, such that it does not negatively affect the influence of those BS's that were detected. It is also expected that the use of weights should improve the results since it further correlates the samples to the database according to its level of importance.

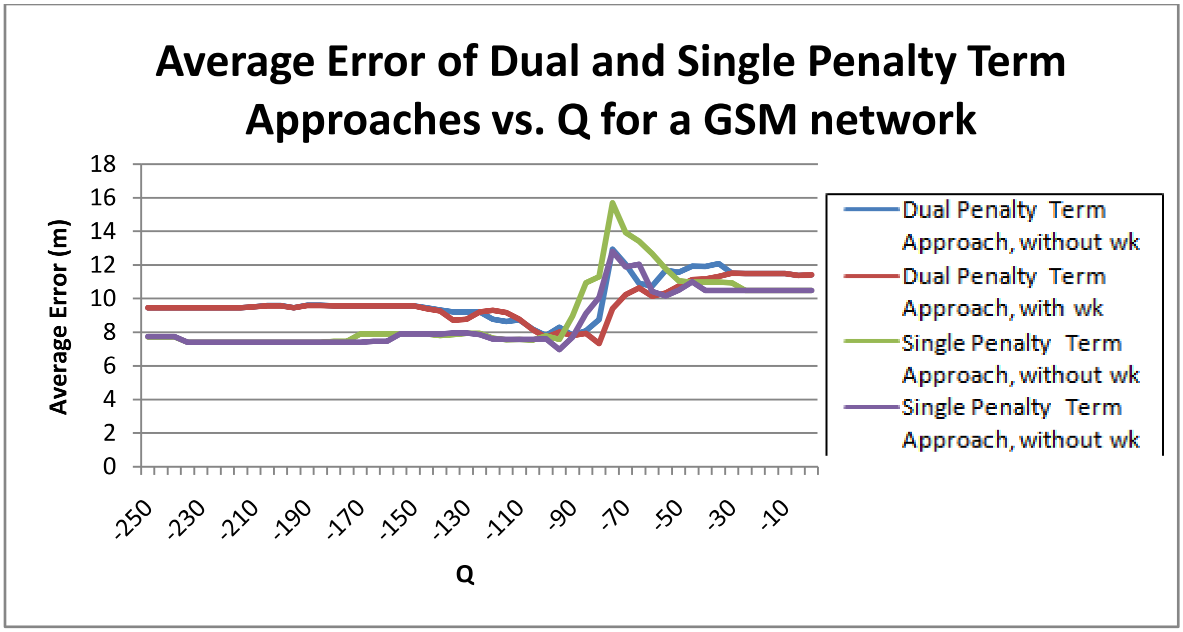

Figure 38: Average error of Dual and Single Penalty Term Approaches vs. Q for a GSM network

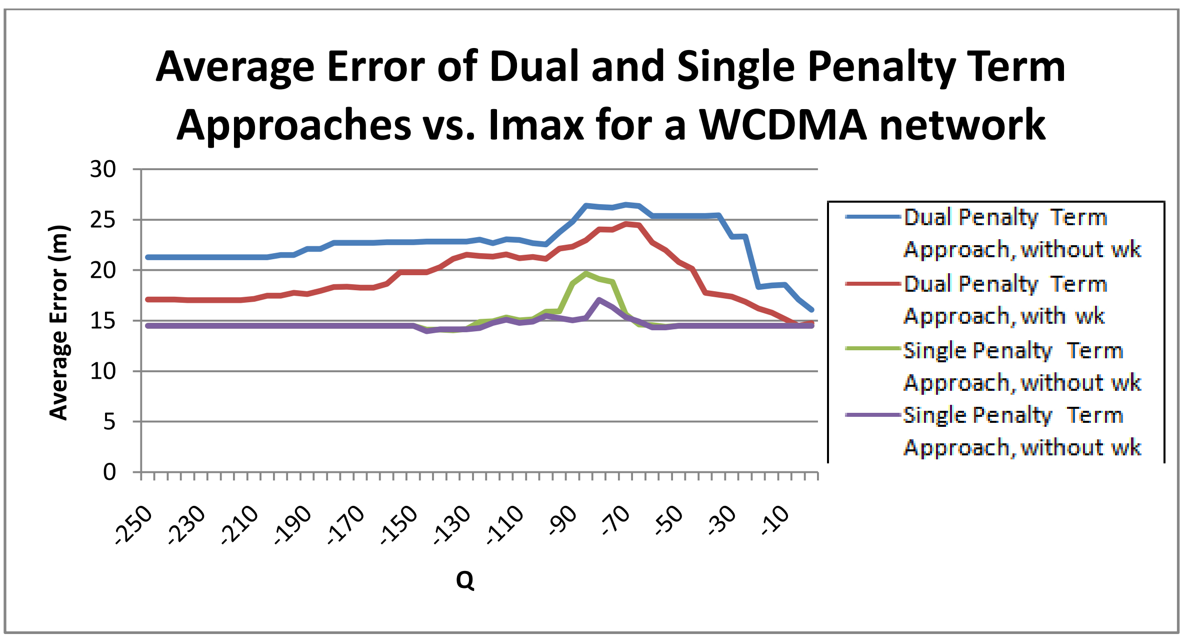

Figure 39: Average error of Dual and Single Penalty Term Approaches vs. Q for a WCDMA network

Figures 40 and 41 above indicate that the average error stabilizes as the value of Q decreases, as expected. Within the range of Q that overlaps with the signal strengths that were detected amongst the common CI's in the fingerprint, an erratic behavior is seen in the graph. This can be explained by the fact that it interferes with the influence of those common detected cells. The smallest value for the average error is obtained within this range, but cannot be used as a reference since it will vary according to the signal strengths obtained in the database fingerprint. Thus, a relatively small value of Q must be selected at a point where the graph tends to stabilize. A constant value of -160 has been selected for Q in this research, as was used for Area A.

Generally, it is seen that the use of weights results in an improvement in the error. The use of weights in the calculations further emphasizes the importance of those BS's that are similar, resulting in this improvement. However, for smaller values of Q, it appears that the weights do not influence the results for the Single Penalty Term Approach. This is due to the fact that the Single Penalty Term Approach emphasizes those CI's that are common, more than the Dual Penalty Term Approach does. The purpose of the weight is to do just this, and thus it has already been catered for and does not influence the results greatly.

The average number of estimates obtained for varying values of Q in a GSM network and WCDMA network are portrayed by Figures 42 and 43 respectively. It is expected that the values of Q that overlap with the range of signal strengths within the common detected BS's of the fingerprint will cause erratic behaviors in the average number of estimates. This is as a result of this value of Q interfering with the signal strengths of the detected CI's. The use of weights is expected to reduce the average number of estimates by further classifying the sample according to the cost factor of both the GSM part of the fingerprint, as well as the WCDMA part of the fingerprint.

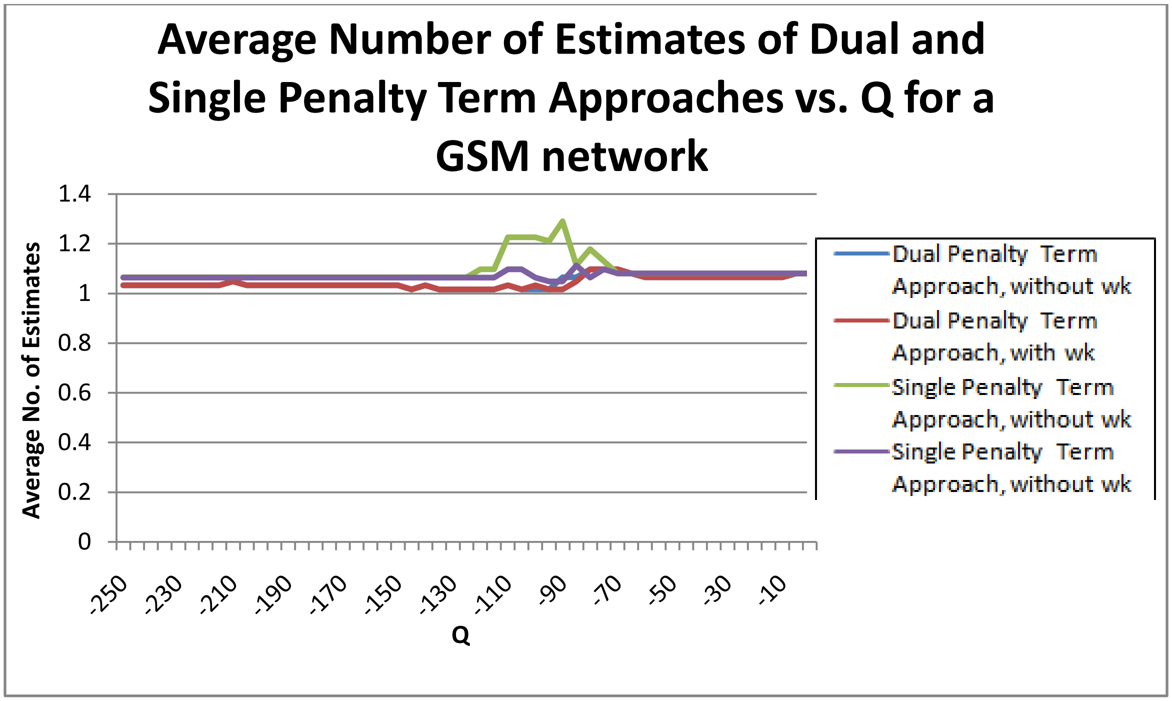

Figure 40: Average number of estimates of Dual and Single Penalty Term Approaches vs. Q for a GSM network

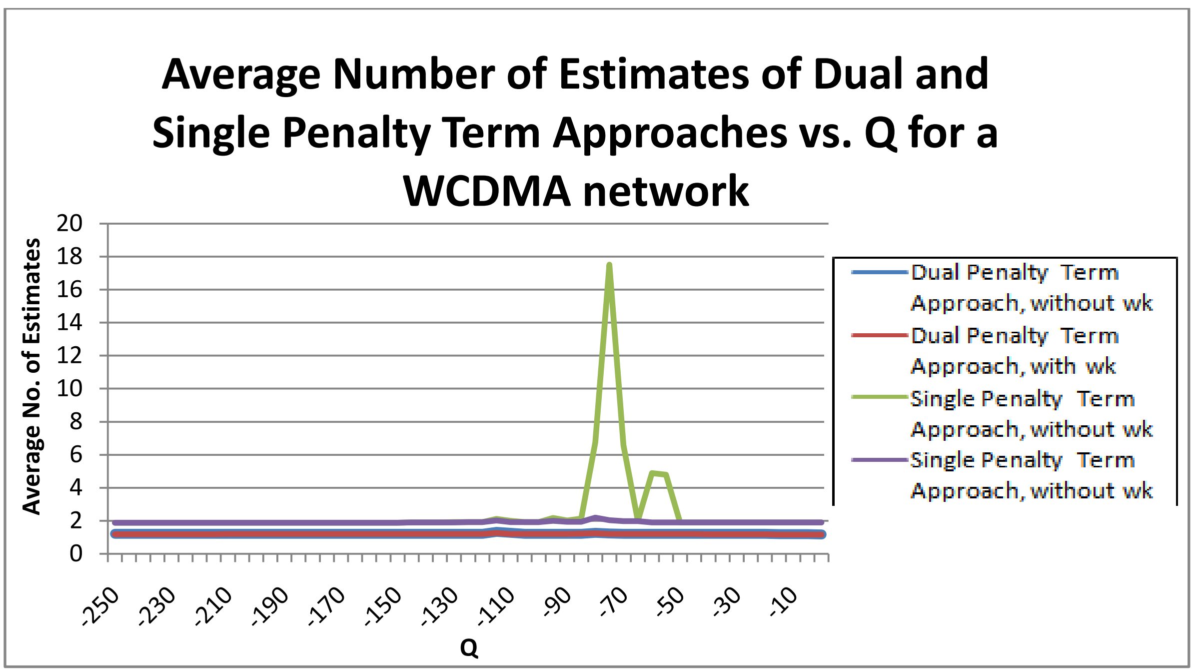

Figure 41: Average number of estimates of Dual and Single Penalty Term Approaches vs. Q for a WCDMA network

From Figures 42 and 43, it can be seen that the results are as expected. For values of Q within the range of Q that overlaps with the signal strengths of the common CI's, high values are obtained for the number of estimates for the Single

Penalty Term Approach. However outside of this range, weights do not seem to influence the results at all. In addition, within this range, the use of weights tends to stabilize the results for the Single Penalty Term Approach by adding another factor for the correlation of the sample with the database fingerprint. The Dual Penalty Term Approach already further classifies the sample points since it uses those CI's in the database fingerprint that do not occur in the sample, as well as those CI's in the sample that do not occur in the database fingerprint, in the calculations. Thus the use of weights do not influence the results since it gives importance to the number of common CI's. This has already been emphasized in the calculations as mentioned above and it thus eliminates more of the possible fingerprint estimates. However, even though there is a reduction in the number of possible estimates in this overlapping range, the Dual Penalty Term Approach still yields a higher level of errors. By selecting a value of -160 for Q, it does not fall into the overlapping range and stable results are obtained for both approaches. These techniques and the influence of weights are analyzed further in section 4.3.4.

4.3.4. Techniques used to Improve the Correlation

As was observed earlier, Area B is predominantly GSM, with WCDMA coverage only properly reaching just under half of the area. This area will give a good indication as to whether the proposed positioning solutions work in any suburban environment, irrespective of its geographical location or whether a WCDMA or GSM network is used.

Figures 44 and 45 give a comparison of the average error obtained for the various techniques with the different networks, without and with map matching respectively. It is expected that the worst results will be obtained for the Strongest Cell technique, since it only uses one CI in the correlation procedure, thus reducing the criteria for comparison. Fifteen different CI's were detected in the entire area for the strongest cells in the WCDMA database fingerprints, while 11 different CI's were detected amongst the strongest cells in GSM database fingerprints. This results in only a coarse division of the area based on the strongest CI. To further define the location, the signal strengths of these strongest CI's are used. However, the signal strength fluctuates considerably and the standard deviation of the signal strengths amongst the strongest neighbours in the WCDMA database fingerprints is only 6.6 and that for the GSM database fingerprints is 12.6. Thus the use of just the strongest CI alone is not enough to distinguish the fingerprints for the correlation procedure.

The best results are expected for the Single Penalty Term Approach since it gives the correct amount of importance to the fingerprints in terms of both those CI's that are common between the database and sample fingerprints, as well as those that are not common. The Dual Penalty Term Approach is expected to put too much emphasis on those fingerprints that are not similar and thus may distort the cost function.

The Multiple Weights approach is expected to yield better results as it adds further features to match the sample with the fingerprints. Clustering is expected to better the results obtained from the Strongest Cell approach, since it correlates the signal strength from the serving cell of the sample with clustered fingerprints, instead of individual fingerprints. These clustered fingerprints consist of two geographically adjacent single fingerprints and the sample signal strength is correlated to both these fingerprints in the clusters, thus reducing the chance of outliers.

Figure 46 illustrates the average number of estimates obtained. The highest number of estimates is expected for the Strongest Cell method since it only provides a course resolution of the area as mentioned above. For each strongest CI, there is only a small standard deviation in the signal strength as seen earlier. Thus the signal strength of the strongest CI does not fluctuate greatly. This means that there are several cases where the test fingerprint will be incorrectly estimated since the closest matching signal strength for the same CI is used. In addition, multiple estimates are also easily made. Moreover, the signal strength tends to fluctuate in one particular location due to noise and interference. For this reason, multiple measurements need to be taken at any one location point and the average of these should be used to form the database fingerprint. Therefore, the poorest results are expected for the Strongest Cell method since it just uses the strongest detected CI.

Since this is a predominantly GSM area, the use of GSM data is expected to produce better results. This is reinforced by the fact that in the majority of the location points, only a few WCDMA neighbours were detected. The use of the combined networks is expected to give the best results in terms of both the average error as well as the average number of estimates since it now has double the criteria in which to match the samples to the fingerprint. Furthermore, it is anticipated that using the combination of networks will result in less estimates being made.

The Exponential term approach is expected to yield poorer results in terms of average errors since it assumes that those CI's from the database that are not detected in the sample, should be given a signal strength value equal to the lowest signal strength in the sample fingerprint. However, this tends to interfere too greatly with the influence of those CI's that are common. In addition, giving these uncommon CI's this higher value of signal strength also incorrectly implies that it would have been detected in the sample.

The use of only the common BS's is expected to result in lower accuracies levels than Approaches 1 and 2. As mentioned in section 3.5.2, those CI's that are not common should be penalized. It is expected that as in the Single Penalty Term Approach, more importance should be given to how much of the sample is matched by the database fingerprint, and not how much of the fingerprint has been matched by the sample as well. The Dual Penalty Term Approach gives too much emphasis on those CI's that are not common between the database and sample fingerprints, such that the power of the more important common CI's get drowned out.

Map matching is expected to improve the results to some extent. The errors produced by the GPS measurements are now catered for since the points are now matched to an existing grid. This also means that it is unlikely that there will be an improvement in the number of estimates that are made.

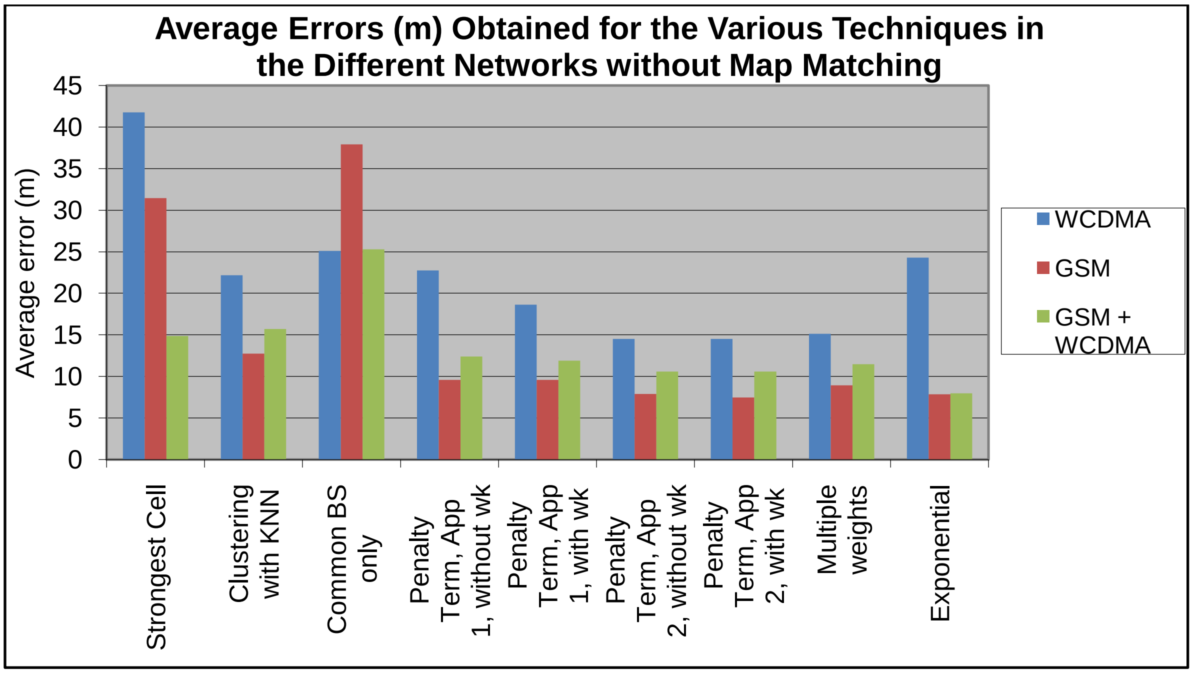

Figure 42: Average Errors obtained for the various techniques in the different networks without map matching

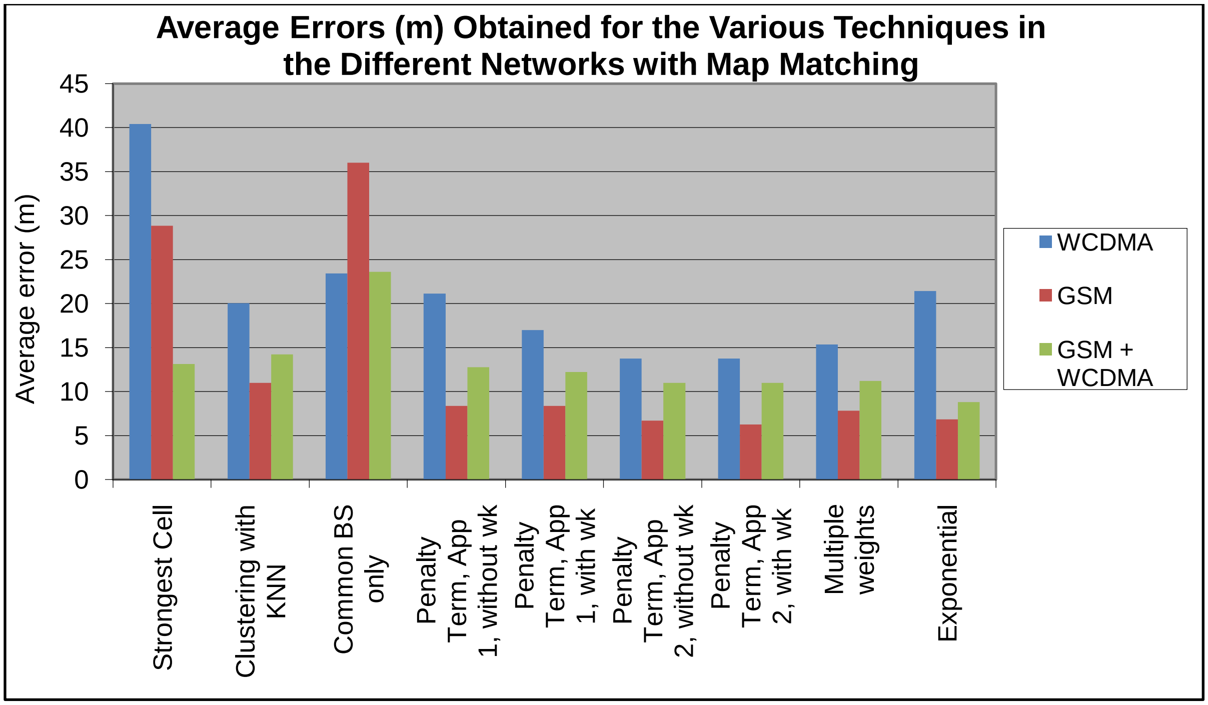

Figure 43: Average errors obtained for the various techniques in the different networks with map matching

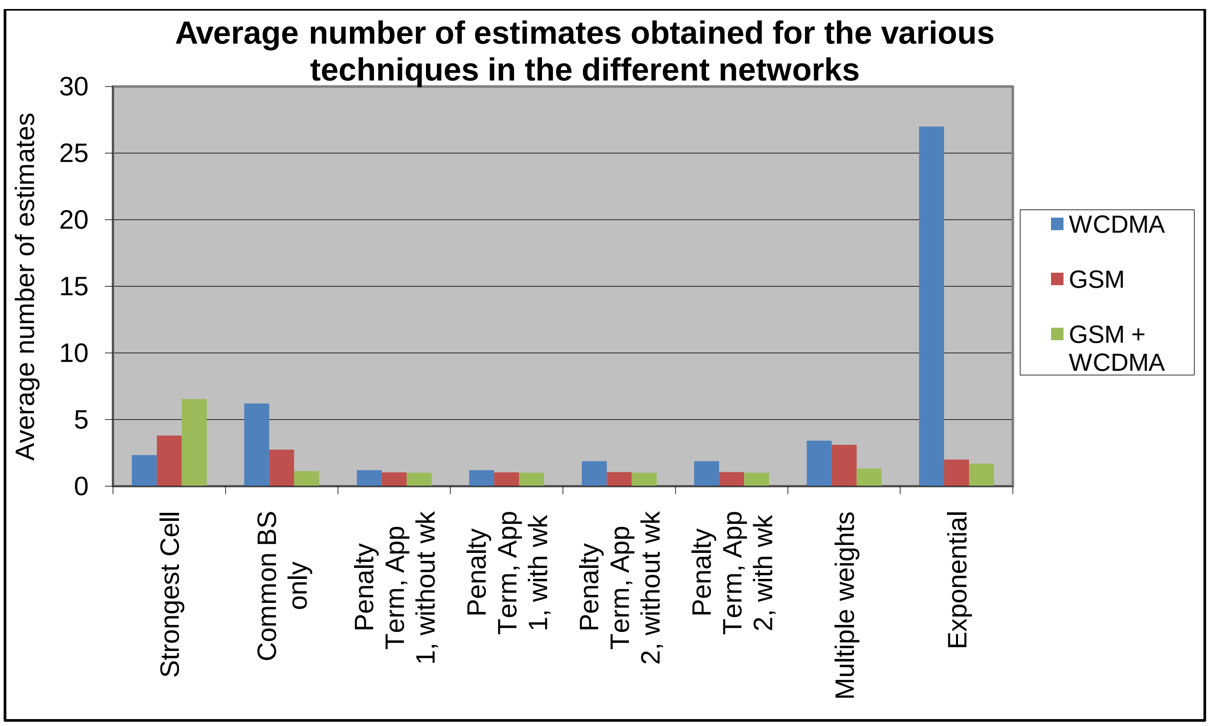

Figure 44: Average number of estimates obtained for the various techniques in the different networks with/without map matching

Clustering reduced the error of the Strongest Cell method to an average of 50.7%. The improvement was as predicted since this process eliminates outliers.

The Exponential approach yielded a very high number of average estimates. This is a result of its definition of a cost function that is not unique enough to distinguish the differences between the fingerprints in the database. Thus the average error cannot be used as a true reflection of the performance of this technique. Multiple estimates are made since the penalty term is chosen to equal the smallest value of the sample fingerprint and thus interferes with the cost function and causes it to be unstable. Thus a large number of estimates are made when the cost function does not correlate the sample and database fingerprints accurately. Nevertheless, it can be established that the Exponential approach is not a reliable method in Area B since, it is not realistic to obtain many possible estimates in a practical situation.

The average number of estimates did not change with map matching. This is as expected, since map matching just corrects the position of the fingerprints slightly. The use of map matching reduces the error to around 94%.

Figure 44 shows that the Strongest Cell approach yields the poorest results as predicted for WCDMA and the combined networks. However, the common CI only approach produced the poorest results for the GSM network. This is due to the fact that this area is dominated by GSM, which results in many fingerprint locations containing common CI's, especially since there was only 10 different CI's that were picked up in the entire area. For this reason, those CI's that are not common between the sample and database fingerprint become very valuable in the cost function.

The best results were obtained for the Single Penalty Term Approach, for the GSM network as was expected. The Single Penalty Term Approach also produced the best results for the WCDMA and combined networks and it was noted that weights did not influence the results here. In general, GSM provides better results. This is as expected since this is a predominantly GSM area and the WCDMA neighbours were scarce to measure. Using the combined network seems to incorporate the higher errors obtained from the WCDMA network as predicted.

Observing the overall results indicates that the combined use of both networks reduces the number of estimates as was foreseen. However, there was an increase in the number of estimates for the Strongest Cell method for the combined networks, compared to the GSM network. This is due to the very high number of estimates that were made for the GSM case. In addition, this is a predominantly GSM area, thus the influence of the GSM difference term may be much lower than that of the WCDMA network, thus having a greater influence. It is thus seen that use of the combination of both networks may not necessarily be the best solution in terms of accuracy since the errors in both the networks get incorporated.

4.4. Summary

Tables 9 to 11 in Appendix B indicate the location accuracies produced by the techniques in each of the networks. These accuracies are represented by R67, R95 and the RMSE values respectively. The notation MM refers to map matching in these tables.

Although it is ideally hoped that the signal strengths are constant at each location point, and that it is only dependant on location, it was discovered that it tended to fluctuate a bit and was time dependant. This meant that the signal strength varied slightly as time passed. This could be a result of the fact that the environment is not perfect, as well as due to factors such as moving cars on the road and multipath propagation, which result in variations in the signal strengths. The lower levels of accuracy in practicality can also be due to shadow fading which can result for example from the varying position of the handset against the ear. This together with the position at which the antenna is directed can result in an error in the received signal strength of about 5 – 10dB [56]. For this reason, Kemppi [18] used the mean value of the measured signal levels at each location point to form the fingerprints.

Kemppi [18] tested a DCM method based on the Least Means Square method in both GSM and UMTS networks in the suburban area of Olari in Finland, as well as in the more densely built urban area of Helsinki. This method was carried out in the research conducted by the author as the Dual Penalty Term Approach without weights. Table 5 shows a comparison between the R67 and R95 values obtained for this approach in Area A and Area B in the research conducted by the author, and the work done by Kemppi in Olari.

Network	**R67 (meter)**			**R95 (meter)**			**RMSE (meter)**		
	Olari [18]	**Area A**	**Area B**	**Olari [18]**	**Area A**	**Area B**	**Olari [18]**	**Area A**	**Area B**
UMTS	131	28.48	27.65	388	43.19	59.28	168	24.66	30.65
GSM	71	13.89	7.96	284	20.68	36.76	196	15.01	17.9
UMTS + GSM	66	18.25	11.34	162	43.19	53.26	84	22.51	19.41

Table 5: Comparison of the results obtained in this research, as well as by Kemppi [18] for the Dual Penalty Term Approach without weights and without map matching

The average RMS results obtained in the urban area were 169.5m, 106.5m and 78.5m for the UMTS network, GSM network and UMTS + GSM network respectively. In general, there is an improvement in the result for the urban area.

An approach similar to the Dual Penalty Term Approach without weights presented in this research was carried out by Lakmali *et al* [25, 26] in GSM networks of Sri Lanka in an urban area in Colombo, a suburban area in Moratuwa (Sri Lanka), as well as in a rural area in Kurunegala. Where WkNN was not used, mean errors of 137m, 296m and 269m were obtained for urban, suburban and rural areas respectively. This compares with the RMSE obtained in this research of 15.01m and 17.9m for the suburban Area A and Area B respectively, as is given in Table 5.

Borkowski [1] analyzed the Pilot Correlation Method in the UMTS network of Tampere in Finland*.* The R67 results that were obtained for the urban and suburban environments were 70m and 170m respectively. The Common CI's technique carried out in this research is similar to Borkowski's Pilot Correlation Method. R67 values of 36.88m and 25.15m were obtained for the Common CI's approach in this research for Area A and Area B respectively, in the WCDMA network of a suburban environment.

From these observations, it is safe to say that the Dual Penalty Term Approach algorithm that was carried out in the research conducted by the author, will work in an urban area too and possibly obtain higher levels of accuracies in the urban area. Tables 9 to 11 in Appendix B indicate that the Single Penalty Term Approach obtained a lower value for RMSE than the Dual Penalty Term Approach. Thus it can be deduced that the Single Penalty Term Approach would also produce good results in an urban area. From the tests carried out by Lakmali *et al* [25, 26], it appears that the suburban area is the worst performing, with the rural area following close behind. This was due to a low BS density in these areas. Kemppi had an average number of hearable cells of as low as 1.8 per fingerprint in the suburban area [18]. However, the suburban areas covered in this research appeared to have sufficient Node B's or BS's that were picked up to still obtain accurate results. Generally in rural areas, only an omnidirectional serving cell can be measured and the BS's are located far away from each other [58]. Thus, contradictory to the results obtained by Lakmali *et al*, a much lower level of accuracy is expected to be observed for these areas. It is also observed that the clustering method may prove to be efficient in improving the accuracy in the rural areas.

Khalaf-Allah [57] estimated the database fingerprints for a suburban area in Hannover (Germany) using a 3D deterministic wave propagation model. This calculates the distance from the handset to the BS, using the TA measurement, while catering for the error that may result from the large steps in TA. This will reduce the area of search. In the tests carried out by Khallaf-Allah [57], it was discovered that the maximum likelihood estimate (which is taken in this research), is highly sensitive to any inaccuracies in the database. In addition, estimating the location based on correlation of received signal strengths alone could mean that there are multiple areas with similar levels of correlation. These candidates must then further be arranged according to which is more likely. Without further processing, a mean error of 248m was obtained for this technique. This was obtained for tests where the database was created using 3D wave propagation models.

In the work done in this research conducted by the author, computational time was not an issue. However, in the actual implementation of this system, there is a large amount of fingerprints in the database which has to be processed. To help reduce the processing time, the TA values can also be included in the database [57]. Only the area that matches the measured TA value will be considered for the location estimation.

Compared to research done previously, higher accuracies are obtained in the research done by the author. This is due to the many BS's or Node B's that were detected in this research. A common problem which was encountered in the research done previously was the lack of sufficient base stations.

At locations that are near a cell's edge, there is a higher possibility of errors since the measurements tend to be more similar.

From Tables 9 to 11 in Appendix B it can be seen that in general the Single Penalty Term Approach obtained the best results. The inclusion of weights does no harm and only strengthens the cost function. Even though the Strongest Cell technique produced the lowest level of accuracy, it still provided satisfactory results and can thus be used in rural areas where only the serving cell is generally detected. In addition, the Clustering technique can generally improve these results as seen in these tables.

It was noted that even though the Exponential approach appears to yield decent levels of accuracies, it is prone to obtain too many average number of location estimates. The Multiple Weights approach is also observed to yield excellent results.

A shortfall of this method is that as the environment changes, the database has to be updated. Thus it may be necessary to update the database at an interval of 6 to 12 months. For this reason, in areas where high accuracies are not required, it may be more feasible to use propagation models to construct the database.

Overall, better results are obtained in Area B than Area A for a WCDMA network. On the other hand, Area A shows better accuracies than Area B for a GSM network. Even though the use of a combination of the two networks may not produce the lowest error levels overall, the accuracy levels are still quite good. Thus it can be concluded that using a combination of the two networks is a safer approach in case the network is predominantly GSM or WCDMA.

5. Conclusion and Recommendations

The aim of this research was to study, develop algorithms and test a suitable method for cellular positioning in South Africa, a developing country. The pattern matching approach was investigated due to the benefits it yields in terms of being able to acquire good levels of accuracies with no changes required to be made to a handset. This is particularly essential in a developing nation where it is unrealistic to expect every member of the population to purchase a new handset.

The focus was limited to analyzing various methods of obtaining the cost function in suburban environments. Suburban areas in the neighbourhoods of Lynnwood in Pretoria, and SE 1 in Vanderbijlpark were covered under similar conditions. However, the area in Lynnwood had predominantly WCDMA coverage, while that in SE 1 had mainly GSM coverage. This would give an indication of the feasibility of the pattern matching technique in any suburban area, irrespective of its dominant network type.

Since very high accuracies cannot be obtained by simulating the environment using propagation models, field tests were conducted to construct the database instead. The signal strengths and indicating parameters of the CI's were used as the features to form the database. The Timing Advance parameter was not used due to the very coarse measurements it allows. The parameters used are easily available from the network measurement reports and no signaling overhead is needed.

The accuracies obtained in this research are of competitively good levels in comparison with that obtained by other common techniques used in literature surveyed. All the techniques produced relatively good results in both the areas, indicating that it is safe to conclude that these techniques work in any suburban area. In addition, the results obtained do meet the FCC requirements.

The paragraphs below briefly discuss the answers to the key research questions that were formulated in section 3.1, as well as the most significant findings.

Since it is not realistic to obtain too large a number of estimates, the criteria for analyzing the feasibility and quality of the techniques were based on the average error that it produced, as well as the average number of location estimates.

The dominance of the GSM or WCDMA network in an area does influence the results if only one network type is used in the fingerprints. The use of both the networks means that the benefits and flaws of both the networks get incorporated and generally produces the second best results as opposed to using the dominating network data. Even though the use of both the WCDMA and GSM measurements did not produce the best accuracy on the whole, it appears to be the best solution to cater for areas with different levels of coverage.

Where multiple possible location estimates were made for a network, these had to be further reduced by using the combination of GSM and WCDMA network. Although the use of combined networks saw reductions in multiple estimates in the majority of the cases, this was not always obtained. On the other hand, the techniques which use the neighbouring CI's as well produced very low number of multiple estimates for the combined network.

Although the Exponential approach generally obtained good levels of accuracies, it is prone to acquiring too many estimates, indicating that the cost function is too vague to correlate the sample and database fingerprints. The Multiple Weights approach produced excellent results.

Although the tests were limited to a suburban area, a comparison of the results obtained in this research and work done previously [18, 25, 26] should give an indication as to whether these techniques will work in any type of environment. This comparison of results enables one to conclude that the Penalty Term Approaches will work in both urban and suburban areas [25, 26]. However, the rural areas may see a decline in accuracy since usually only the serving cell can be measured in this environment. Even though the Strongest Cell technique produced the lowest levels of accuracies, it still yields satisfactory levels of accuracies. On the contrary, the Clustering technique provided significantly better results than the Strongest Cell technique and is beneficial for rural areas where only the strongest cell is detected.

This comparison with work done previously also shows that the results obtained in this research yielded significantly lower errors. This is a result of a higher number of BS's or Node B's being detected in these areas. The greater the density of the BS's or Node B's, the more favourable it is for the pattern matching process [1], since it increases the features that have to be correlated.

In contrast to research done previously with respect to the Dual Penalty Term Approach, this research proved that the cost function should include the uncommon CI's between the sample and database fingerprints, as well as the common CI's in the correct proportion. This correct proportion was obtained in the Single Penalty Term Approach, as opposed to the Dual Penalty Term Approach.

Map matching only saw a slight improvement in accuracy by correcting the GPS errors. However, this method is prone to errors when past data is not available to assist in establishing the current position.

Ultimately the best and most stable results in terms of both accuracy and average number of estimates were obtained using the Single Penalty Term Approach. The inclusion of weights in the Penalty Term Approaches saw either no change to the results or an increase in accuracy. Therefore the use of weights proves to do no harm and only strengthens the cost function for the correlation procedure.

Thus the most practical method with good levels of accuracy is the Single Penalty Term Approach in the combined networks scenario for suburban areas and it is anticipated to provide the best results in urban areas as well. The clustering approach is expected to be valuable in rural areas.

A drawback of the pattern matching method is the process of collecting the measurements to construct the database, as well as having to update the database at predetermined intervals or when changes are made in the network configuration. However, the database can be constructed using the measurements taken during the network deployment and optimization phase [59]. Alternatively, propagation models can be used to obtain the fingerprints for the database for areas where precise location estimates are not needed.

Cellular positioning using pattern matching requires far less time to commercialize than many of the other common techniques which require hardware changes and major time consuming changes to be made to the network architecture. Thus it can be implemented relatively easily.

Recommendations for further work include obtaining a greater amount of measurements per location for the database and finding the average of these measurements to form the fingerprints. This was not possible in this research due to the limitations of the field test equipment. A system needs to be implemented to obtain an even distribution of the fingerprints according to location, in the database. A grid system could be used for this, where fingerprints located between the grid points are averaged. The influence of increasing the density of the fingerprints in the database should be studied. Much larger areas should be covered to determine the processing time. In these cases, the fingerprints should be organized based on the CI's that were detected so that computational time can be reduced. If mobile users have

GPS enabled on their phones, this information can be used together with the RF signal measurements to update the database when the user sends a query. The impact of the various factors such as weather, type of handset, environment and network provider on the pattern matching results should be tested and fully analyzed.

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Appendix A

The following parameters can be obtained by the Field Test Mode in the Sony Ericsson phone. However, not all these parameters have been used in this research.

GSM Cell

The GSM Cell section obtained the following measurements, which are briefly explained in Table 6 and described in more detail thereafter.

C	Barf	BS	B	Rxls	C1	C2
MCC	MNC	LAC	Ci	Rac		

Symbol	**Explanation**	**Possible values**
C	Service Type	B: BCCH S: SDCCH s: Hopping SDCCH T: TCH t: Hopping TCH P: PBCCH p: Hopping PBCCH D: PDTCH d: Hopping PDTCH
Barf	BCCH ARFCN for the serving cell	
BS	Base Station Identity Code	
B	Working band	1: GSM900 4: GSM1800
Rxls	Received Signal Strength	
C1	Difference between the current and the acceptable minimum strength for the received signal	
C2	Antenna selection criteria	
MCC	Serving cell Mobile Country Code	
MNC	Serving cell Mobile Network Code	
LAC	Serving cell Location Area Code	
Ci	Cell ID	
RAC	Routing Area Code	

Table 6: Explanation of the symbols used in the GSM Cell section

The Broadcast control channel is a downlink channel that broadcasts system control information [63]. The Standalone Dedicated Control Channel is a point-to-point channel which is dedicated to one UE for transfer of control information and is used for location updates amongst others. The transmission of speech or data is possible due to the Traffic Channel [63]. Packet Control Broadcast Channel is a downlink channel and it broadcasts information about the serving cell and neighbouring cells. This UE makes use of this to access the network [66]. Packet Data Traffic Channel can be either uplink or downlink and is used for the transfer or user information [66].

Frequency hopping is the term referred to when the transmitter changes the carrier frequency of the signal in a certain periodic pattern. Better signal to noise ratios are obtained since the signal experiences a different channel and different noise signals per frequency change [67]. Thus hopping SDCCH, hopping TCH, hopping PBCCH and hopping PDTCH represent the respective channels described above with the addition of frequency hopping.

Absolute Radio Frequency Channel Number for the serving cell is a number that represents the channel and identifies its RF channels [63]. The Base Station Identity Code is a unique code present in the broadcast channel messages, that identifies the Base Station [67]. The working band used by the mobile operator is indicated by either GSM900 or GSM1800.

C1 and C2 are criteria used for cell reselection. C1 is a path loss criterion and determines the minimum signal level for cell reselection in instances where PBCCH is not present in the cell. C2 is used as a criteria for ranking the cells during cell reselection [66].

A Location Area consists of a set of cells that is defined by the mobile operator. A Routing Area is a subdivision of the cells in the Location Area. The Routing Area is used for paging by the GPRS, while the Location Area is used for paging by incoming circuit-switched calls [66]. The Mobile Country Code, Mobile Network Code and the Location Area Code together constitute the Location Area Identification of the cell. This Location Area Identification, together with the Routing Area Code forms the Routing Area Identification [64]. The Cell ID is a unique number that identifies a sector of a Base Station.

GSM Neighbors

The GSM Neighbours section produced the following measurements:

C	Barf	C1	C2
Narf	Nrxl	NC1	NC2
Narf	Nrxl	NC1	NC2
Narf	Nrxl	NC1	NC2
Narf	Nrxl	NC1	NC2
Narf	Nrxl	NC1	NC2
Narf	Nrxl	NC1	NC2

Symbol	**Explanation**
Narf	Neighbouring ARFCN
Nrxl	Neighbouring Received Signal Strength

Table 7: Explanation of the symbols used in the GSM Neighbours section

Table 7 above describes the symbols used in the GSM Neighbours section and is explained below.

NC1 and NC2 refer to the C1 and C2 for the neighbouring cells as mentioned in the section for the GSM Cell measurements. C, Barf, C1 and C2 are as described for the GSM Cell section. NC1 and NC2 refer to the C1 and C2 parameters for the neighbouring cells. Neighbouring ARFCN indicates the Absolute Radio Frequency Channel Number of the neighbouring cell.

Neighbouring Received Signal Strength gives the signal strength of the neighbouring cell.

WCDMA Neighbours

The WCDMA Neighbours section provided the below mentioned measurement parameters. Table 8 explains these parameters briefly.

Uarfc	RSSI	MCC	MNC	LAC
WUarfc		SC	RSCP	EcNo
WUarfc		SC	RSCP	EcNo
WUarfc		SC	RSCP	EcNo
WUarfc		SC	RSCP	EcNo
WUarfc		SC	RSCP	EcNo
WUarfc		SC	RSCP	EcNo

MCC, MNC and LAC are as explained in the GSM Cells section.

Symbol	Explanation	Possible values
UARFC	UMTS Absolute Radio Frequency Channel Number	
RSSI	Received Signal Strength	
W	WCDMA cell type	S: Serving cell A: Active set member M: Monitored neighbour D: Detected neighbour
SC	Scrambling Code	
RSCP	Received Signal Code Power	
EcNo	Carrier to Noise Ratio	

Table 8: Explanation of the symbols used in the WCDMA Neighbors section

Scrambling codes are used to spread the channels, and results in separate identities for transmission in each sector. A Node B can thus transmit at more than one frequency, since the scrambling code allows for the sector to be identified. Each Node B sector is identified using a combination of the UARFCN and the Scrambling Code. Received Signal Code Power is an indication of the signal strength in UMTS networks and is measured in dBm. Carrier to Noise Ratio is the ratio of the RF carrier power and channel noise power [63]. The WCDMA cell types that can be detected in the measurements include serving cell, active set, monitored neighbor and detected neighbor. The serving cell is the cell that the UE has currently chosen after the cell selection/reselection process [35]. The active set members are those cells that the UE connects with during a soft handover [65]. The monitored neighbours represent those cells whose pilot signal to noise ratio is too weak to be added to the active set, but are still monitored by the UE [65]. The detected neighbours are other cells in the network that is detected, but are not used in handover.

Appendix B

The R67, R95 and RMSE values for the various techniques carried out in different networks in Areas A and B are presented in Tables 9 to 11.

TECHNIQUES	67% (m)				95% (m)				RMSE (m)			
	Area A		Area B		Area A		Area B		Area A		Area B	
	No MM	MM	No MM	MM	No MM	MM	No MM	MM	No MM	MM	No MM	MM
Strongest Cell	67.2	67.78	55.94	53.84	79.89	80.61	87.22	85.37	58.5	58.89	51.08	48.72
Clustering, with KNN	15.19	15.97	27.21	26.28	27.38	26.97	54.92	50.01	15.26	15.64	28.26	25.26
Common BS's Only	36.88	36.92	25.15	24.6	47.76	48.41	59.24	50.76	32.46	32.63	30.41	28.03
Dual Penalty Term Approach, without w_k	28.48	28.54	27.65	28.03	43.19	42.21	59.28	50.33	24.66	24.75	30.65	27.35
Dual Penalty Term Approach, with w_k	19.91	20.29	21.22	17.84	43.19	42.21	59.28	49.69	22.49	22.55	26.03	23.45
Single Penalty Term Approach, without w_k	13.12	12.83	14.53	15.29	34.62	34.07	36.57	33.13	16.28	16.37	20.57	18.7
Single Penalty Term Approach, with w_k	13.12	12.83	14.53	15.29	34.62	34.07	36.57	33.13	16.28	16.37	20.57	18.7
Multiple weights	13.18	13.07	15.44	15.93	28.74	28.78	36.57	31.86	15.28	15.36	20.06	18.66
Exponential	28.33	30.91	30.52	28.67	53.38	54.01	63.65	52.88	32.73	32.88	30.33	27.49

Table 9: Comparisons of the accuracies of the methods for a WCDMA network

TECHNIQUES	67% (m)				95% (m)				RMSE (m)			
	Area A		Area B		Area A		Area B		Area A		Area B	
	No MM	MM	No MM	MM	No MM	MM	No MM	MM	No MM	MM	No MM	MM
Strongest Cell	40.71	54.05	40.52	37.59	72.37	71.07	60.35	63.07	46.92	47.08	37.22	34.23
Clustering, with KNN	10.99	14.35	14.24	12.74	24.04	23.74	56.6	41.09	15.81	15.55	20.37	16.01
Common BS's Only	37.39	37.38	47.22	46.13	52.1	60.07	75.37	73.97	37.13	37.34	44.9	40.86
Dual Penalty Term Approach, without w_k	13.89	13.62	7.96	8.28	20.68	29.24	36.76	28.03	15.01	14.87	17.9	12.28
Dual Penalty Term Approach, with w_k	13.89	13.62	7.96	8.28	20.68	29.24	36.76	28.03	15.01	14.87	17.9	12.28
Single Penalty Term Approach, without w_k	13.89	13.62	6.24	6.37	20.68	32.54	36.25	28.03	15.43	15.32	14.44	10.64
Single Penalty Term Approach, with w_k	13.89	13.62	6.24	6.37	20.68	32.54	25.93	22.94	15.43	15.32	13.73	9.66
Multiple weights	16.61	16.22	9.01	9.78	24.94	28.89	26.37	20.39	17.33	17.21	16	11.06
Exponential	16.61	16.22	6.12	6.37	35.16	33.79	21.15	20.39	17.89	17.68	14.5	9.7

Table 10: Comparisons of the accuracies of the methods for a GSM network

TECHNIQUES	67% (m)				95% (m)				RMSE (m)			
	Area A		Area B		Area A		Area B		Area A		Area B	
	No MM	MM	No MM	MM	No MM	MM	No MM	MM	No MM	MM	No MM	MM
Strongest Cell	20.63	20.55	14.7	14.33	31.52	31.55	38.68	30.02	18.35	18.39	22.32	15.63
Clustering, with KNN	20.42	20.49	21.37	18.03	34.02	33.77	44.41	41.22	18.73	18.79	33.69	19.26
Common BS's Only	36.72	36.63	30.97	30.33	50.95	50.88	59.19	57.91	32.6	32.66	20.37	30.61
Dual Penalty Term Approach, without w_k	18.25	20.42	11.34	10.39	43.19	41.73	53.26	45.81	22.51	22.38	19.41	17.24
Dual Penalty Term Approach, with w_k	16.61	17.28	11.34	10.39	35.16	34.66	53.26	34.98	20.69	20.56	17.97	16.32
Single Penalty Term Approach, without w_k	12.42	12.8	11.34	11.15	28.48	28.77	32.06	29.12	13.83	13.92	17.97	14.32
Single Penalty Term Approach, with w_k	12.42	12.8	11.34	10.72	28.48	28.77	32.06	28.48	13.83	13.92	18.87	12.75
Multiple weights	13.18	13.07	11.79	12.1	23.50	24.53	34.53	32.49	15.12	15.09	14.59	15.9
Exponential	28.21	28.21	6.19	6.37	53.38	54.01	21.15	20.39	29.84	29.99	22.32	9.85

Table 11: Comparisons of the accuracies of the methods for a WCDMA + GSM network