Multipath Detection Using the Dendritic Cell Algorithm

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SUMMARY

For engineering applications high precision GPS with survey grade receivers allows positioning in real-time to a centimetre level of precision. Many of the error sources affecting the GPS signal have been significantly removed in order to achieve such high precision. However, one error source that is difficult to mitigate is that of the multipath error. GPS signal multipath occurs when the GPS signal arrives at the antenna via multiple paths. This occurs when the GPS signal is reflected off objects in the antenna environment. This is a significant problem when using GPS in an urban environment.

Carrier phase multipath error has a theoretical maximum of approximately 4cm. However, code multipath can be in the order of a few metres to tens of metres in areas of high multipath. This can result in an erroneous carrier phase solution or no phase solution at all. The ability to mitigate this error in real-time will improve the level of accuracy and precision of GPS for surveying, engineering, and other high precision applications. In addition, with the increased use of code GNSS for personal navigation and indoor navigation using high sensitivity GNSS, multipath is even more of a problem in these areas, thus a 'real time' multipath mitigation technique has many mass market applications. Significant research has been conducted in this field both from a hardware and software perspective. Hardware solutions to this problem include the use of choke-ring antennas. However, these are large, cumbersome and expensive (£2,500+). Therefore a software solution that is memory efficiency would be of significant benefit.

This research investigates the use of Artificial Immune Systems (AIS) utilised in computer science, applied to multipath error detection. In particular the deterministic Dendritic Cell Algorithm (dDCA) was tested, in order to identify and mitigate the impact of multipath on GPS data. AIS is a branch of computer science which takes principles derived from the human immune system and applies it to issues such as internet security, etc. The Dendritic Cell Algorithm was developed from the principles of how dendritic cells in the human body work in differentiating between dangerous and safe context. This algorithm has been successfully applied to internet attack identification, as well as for intruder identification in security robots.

This paper shows one of the results of initial tests using the dDCA algorithm on epoch by epoch On-The-Fly (OTF) static GPS data. The results show that the dDCA algorithm has potential benefits in the fight to mitigate multipath in GPS data.

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1. INTRODUCTION

The use of GNSS for surveying, navigation and LBS is increasing exponentially. High grade receivers allow positioning to centimetre level in real-time. The main error sources have been mitigated in high precision GPS processing however the effect of multipath is still an issue. With the increased use of code GNSS for LBS and personal and indoor navigation, multipath is even more of a problem for these applications.

Artificial immune systems are a collection of algorithms inspired by the human immune system. Over the past 15 years, extensive research has been performed regarding the application of artificial immune systems to computer security. In this paper the Dendritic Cell Algorithm is described. This is a novel immune-inspired algorithm based on the function of the dendritic cells of the human immune system. In nature, dendritic cells function as natural anomaly detection agents, instructing the immune system to respond if stress or damage is detected. Dendritic cells are a crucial cell in the detection and combination of 'signals' which provide the immune system with a sense of context. The Dendritic Cell Algorithm is based on an abstract model of dendritic cell behaviour, with the abstraction process performed in close collaboration with immunologists. This algorithm consists of components based on the key properties of dendritic cell behaviour, which involves data fusion and correlation components. It has been shown that the Dendritic Cell Algorithm can perform well as an anomaly detection algorithm and can be applied to real-world, real-time data (Greensmith, 2007), (Greensmith and Aickelin, 2008).

GPS Signal multipath occurs when the GPS signal arrives via multiple paths. This occurs when the GPS signal is reflected off objects in the antenna environment. This is a significant problem when using GPS in urban environments.

There are two types of signal multipath that can occur, namely specular or coherent multipath and diffuse or non-coherent multipath. Diffuse multipath occurs when the GPS signal is reflected off an irregular surface. Its effect may be manifested as an increase of the GPS noise level, however specular multipath which usually occurs off of smooth reflective surfaces, interferes with the direct signal inducing significant systematic errors in the GPS observables. Figure 1 shows multipath on vertical and horizontal surfaces.

Some Characteristics and Effects of GPS Signal Multipath:
It increases the pseudorange and the impact of multipath on the pseudorange can be up to ten times higher than that on the carrier phase. It change the polarisation of the GPS signal from a Right Hand Circular Polarisation (RHCP) to a Left Hand Elliptical Polarisation (LHEP). Low elevation satellite signals suffer more from the effects of multipath (Andreotti, 2007). Due to the signal attenuation and fading effects caused by multipath it has an impact on the Signal to

Noise Ratio (SNR). There is a relationship between the SNR and the phase multipath. (Bilich and Larson, 2007).

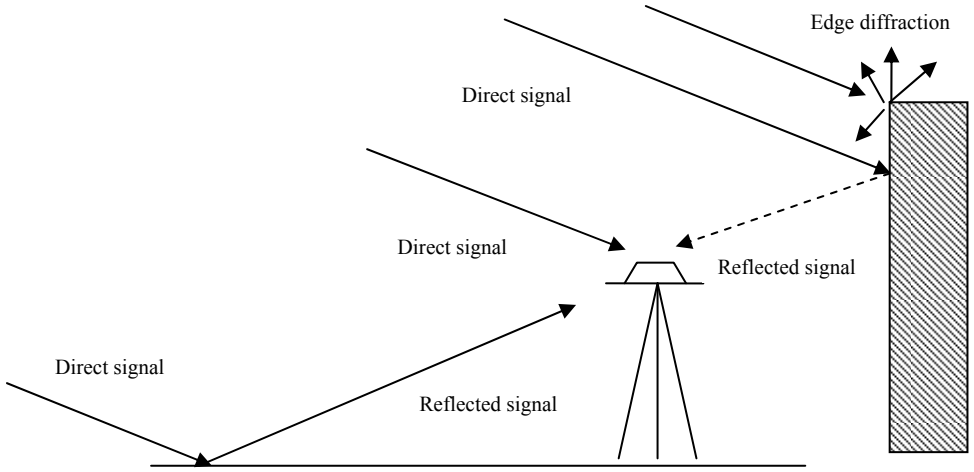

Figure 1: Multipath on Vertical and Horizontal Planar Surfaces

The results shown in this paper are from a 3.5 months "Bridging the Gap" Engineering and Physical Sciences Research Council (EPSRC) funded project. The Bridging the Gaps program was aimed at fostering interdisciplinary research. This project brought together researchers from Computer Science (with biology background) and the Institute of Engineering Surveying and Space Geodesy (IESSG). The logic behind applying the DCA for multipath identification was that the multipath in the GPS time-series can be considered as analogous to an infection in the human body or an anomaly in an internet or robotics context and that this algorithm may have potential to identify and mitigate the presence of multipath in both static and kinematic GPS data.

2. THE DENDRITIC CELL ALGORITHM

2.1 DCA Overview

Artificial Immune Systems (AISs) have developed significantly over the past five years, instigated by the creation of novel algorithms termed '2nd Generation AISs'. One such 2nd Generation AIS is the Dendritic Cell Algorithm (DCA), which is based on models of the dendritic cells (DCs) of the human immune system.

Metaphorically, DCs are the crime-scene investigators of the human immune system, traversing the tissue for evidence of damage - namely signals, and for potential suspects responsible for the damage, namely antigen. As with all things biological, it takes multiple DCs presenting multiple antigens to multiple effector T-cells for an actual response to be mounted. The combination of the population dynamics, signal processing and the correlation between signals and antigen make this system an effective and interesting metaphor for use

within AIS. More information regarding the function of natural DCs can be found in (Lutz and Schuler, 2002) with a distilled version for computer scientists presented in (Greensmith, 2007).

2.2 DCA Abstraction

The DCA is derived from an abstract model of DC biology. The resultant algorithm is population based, with each cell in the population assigned a lifespan value, which is decremented upon the receipt of signal input. Different cells process signals acquired over different time periods, generating individual 'snapshots' of input information. When aggregated across the population, antigens are classified on the basis of the consensus opinion of whether a particular type of antigen is normal or anomalous. This time window effect may be responsible for the robust detection shown by the DCA. The robust detection and correlation performed by the DCA makes it a contender for the analysis of noisy, time-ordered data.

The majority of research performed with the DCA has been within the sphere of security. In particular, the works of Greensmith *et al*. have focussed on computer security applications. The algorithm to date has been successfully applied to port-scan detection (Greensmith *et al*, 2006), (Greensmith *et al*, 2008a), (Greensmith *et al*, 2008b), and upon comparison to a self organizing map performed well on the large dataset used, classifying 13 million antigens in under 100 seconds. In addition, the DCA has also been applied to the detection of a novel threat on the internet, botnets (Al-Hammadi, 2008), where the DCA produced high rates of true positives and low rates of false positives in comparison to a statistical technique.

The DCA is also showing promise in the area of robotic security as demonstrated by Oates *et al*. (2007) where a proof of concept experiment demonstrated that the DCA could be used for basic object discrimination in laboratory conditions. The major outcome of this research is that the DCA is sufficiently lightweight that it can be run on a physical system such as a robot where it can run without draining processing resources and hence has a negligible effect on the resources required for the lower level functions such as steering and image processing.

2.3 Introducing Dendritic Cells

2.3.1 Danger, Death and Dendritic Cells

DCs are the Crime Scene Investigators of the body. They process danger and safe signals. They collect suspect proteins called ***antigens***. They then correlate antigen suspect with signal evidence. Appropriate responses are then generated, either activation or suppression.

2.3.2 Signals

Natural DCs are able to detect the "context" of their resident tissue. Cells in the neighbourhood can die two different ways:

- Necrosis – bad unplanned death from injury or infection
- Apoptosis – controlled death for cell number regulation

Necrotic death produces “danger signals”. Apoptotic death produces “safe signals”. DCs can sense either a safe or dangerous context while collecting antigens.

2.3.3 Underlying Abstraction Model

DCs exist in one of three states: immature, semi-mature and mature. The mature state is used to assess context.

Table 1: DC States and Function

Function	Immature	Semi-mature	Mature
Process input signals	✓		
Collect antigen	✓		
Present antigen to T-cells		✓	✓
Express activating output signals			✓
Express suppressing output signals		✓	

Input signals are combined with a second source of data, such as a data item ID, or program ID number, or GPS epoch number in this application. This serves as the ***antigen***. This is achieved through using a population of artificial DCs to perform aggregate sampling and data processing. Using multiple DCs means that multiple data items in the form of antigen are sampled multiple times. If a single DC presents incorrect information, it becomes inconsequential provided that the majority of DCs derive the correct context. The sampling of data is combined with context information received during the antigen collection process. A graphical representation of this process can be seen in Figure 2.

Different combinations of input signals result in two different antigen contexts. Semi-mature antigen context implies antigen data was collected under normal conditions, whereas a mature antigen context signifies a potentially anomalous data item. The nature of the response is determined by measuring the number of DCs that are fully mature, represented by a value, MCAV - the mature context antigen value. The MCAV is used to assess the degree of anomaly of a given antigen. By applying thresholds at various levels, analysis can be performed to assess the anomaly detection capabilities of the algorithm.

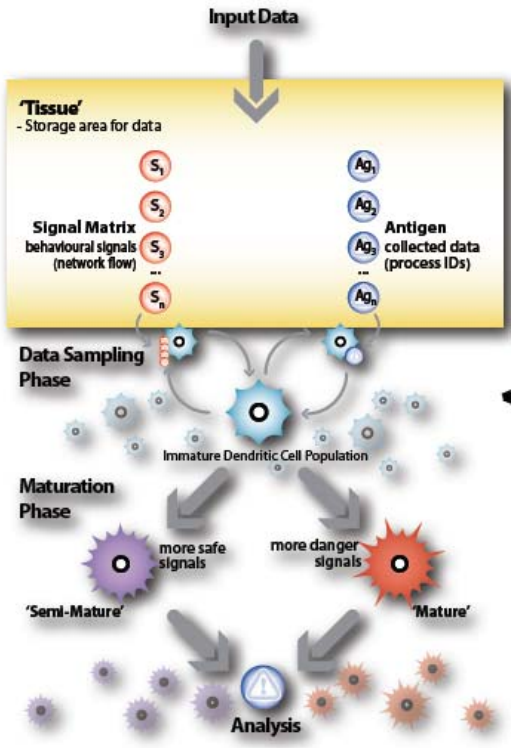

Figure 2: Illustration of the DCA Showing Data Input, Continuous Sampling, the Maturation Process and Aggregate Analysis.

2.4 The Deterministic Dendritic Cell Algorithm (dDCA)

In the deterministic version of the DCA some of the stochastic elements have been removed without adversely affecting its functionality. Previous versions of the DCA featured in excess of 10 parameters, each of which were derived from empirical biological observation and through sensitivity analysis. The resultant deterministic algorithm contains three parameters.

The dDCA signal processing procedure is shown in Equations 1 and 4, where S and D are the input value for the safe and danger signals respectively with (2) and (3) showing subsequent derivation thereof, csm is the interim costimulation output signal and k is the interim context output value. Pseudocode for the implemented dDCA is given in Algorithm 1.

$$csm = S + D \quad (1)$$

$$k = (\text{mature} - \text{semi-mature}) \quad (2)$$

$$k = (D - S) - S \quad (3)$$

$$k = D - 2S \quad (4)$$

input: Antigen and Signals
output: Antigen Types and cumulative k values

```
set number of cells;
initialise DCs();
while data do
    switch input do
        case antigen
                antigenCounter++;
                cell index = antigen counter modulus number of cells ;
                DC of cell index assigned antigen;
                update DC's antigen profile;
        end
        case signals
                calculate csm and k;
                for all DCs do
                    DC.lifespan -= csm;
                    DC.k += k;
                    if DC.lifespan <= 0 then
                                log DC.k, number of antigen and cell iterations ;
                                reset DC();
                     end
                end
            end
    end
end
for each antigen Type do
     calculate anomaly metrics;
end
```

Algorithm 1: Pseudocode of the deterministic DCA.

3. DCA Applied to GPS Data

One of the initial definition challenges in order to apply this routine to GPS data with the goal of multipath detection was the ability to answer the question: "*What are my danger and safe signals, as well as antigens, in a GPS context*?

The dDCA requires two input signals, the 'safe' and 'danger' signals. The safe signal is that which is high when the context is good and low when the context is bad. While the danger signal is high when the context is bad and low when the context is good. In this application the context will be the presence of multipath. The Range Residual (RR) is computed as:

$$RR = \left(\frac{\rho_i - \rho_{(i-1)}}{\lambda} \right) - \left(\phi_i - \phi_{(i-1)} \right) \tag{5}$$

where ρ is the code pseudo-range, Φ is the phase, i is the current epoch and λ is the L1 or L2 carrier phase wavelength (Roberts, 2007), (Ogundipe, 2003).

The RR increases in the presence of high multipath, thus it is used as the danger signal. The SNR increases when there is a strong line-of-sight signal and decreases in the presence of noise and multipath. Thus the SNR was used in the dDCA as the safe signal.

In the human body the dendritic cells are *antigen presenting cells*. Without antigens the dDCA will have no context. In our case, the antigen types have been created by grouping data epochs. So antigen type A1 = epochs 1 to 5, A2 = epochs 3 to 7 and so on. Using overlapping epochs in the antigen types.

3.1 Data Preparation and Normalisation

The RR for each SV was computed and the absolute value taken. The RR along with the SNR data were then normalized into the range 1 – 10 using the linear 'min – max' normalisation based on the equation.

$$y' = \left(\frac{y - \min 1}{\max 1 - \min 1} \right) (\max 2 - \min 2) + \min 2 \qquad (6)$$

Where min 1, max 1 are the original minimum and maximum and min 2, max 2 are the new minimum and maximum.

The dDCA program was run using 100 artificial dendritic cells with a maximum lifespan limit of 100 csm signal units. (This value has been used with success in internet security applications)

3.2 Anomaly Metrics: MCAV and K_α

There are two outputs for the dDCA, the MCAV and K alpha (K_α.). The mature context antigen value (MCAV) is calculated once all data is processed, derived from the output of the cells collected during run-time. This value is generated for each antigen type (α.), where α. is defined as a set of antigens of identical value. The MCAV is a measure of the proportion of antigen presented by a fully mature cell as shown in Equation 7, where $MCAV_\alpha$. is the MCAV for antigen type α., M is the number of 'mature' antigen of type α., and Ag is the total amount of antigen presented for antigen type α.

$$MCAV_\alpha = M/Ag \qquad (7)$$

This metric returns a value between zero and one, where the probability of an antigen type being anomalous increases as this value tends to one. This is a convenient, normalised output, to which an anomaly threshold can be applied. However, it fails to encapsulate the magnitude of the difference between positive and negative values of the presented $\bar{k}$.

K_α is implemented with the dDCA, and uses the magnitudes of the $\bar{k}$ values. This generates real valued anomaly scores and may assist in the polarisation of normal and anomalous processes. The process of calculating this anomaly score is shown in Equation 8, where k_m is the $\bar{k}$ value for DC_m, α_m is the number of antigen presented of type α by DC_m.

$$K\alpha = \frac{\left(\sum_m k_m\right)}{\sum_m \alpha_m} \tag{8}$$

For the GPS data input configuration utilised in the DCA and presented in this paper, the MCAV did not prove useful. However the Kα appeared to provide more useful information.

3.3 GPS Data Test Results – Multipath Detection

GPS data collected using a low cost single frequency UBLOX high sensitivity GPS receiver. About 4 minutes of static data (1 Hz) was collected at a point close to the road and the old IESSG building. A survey grade Thales antenna was used, this would have mitigated some of the multipath in the GPS signal, however even with this antenna there was still a significant component of multipath that remains.

Figure 3: Test Location with Ublox L1 GPS Receiver and Thales Antenna

The data for SV26 was analysed and the results are shown. Figure 4 shows the normalised input signals and its evolution as the input signals are mixed in the dDCA to form the csm and the k intermediary signals. Recall that:

csm = S + D (1)
k = (mature – semi) = (D - S) – S = D - 2S (4)

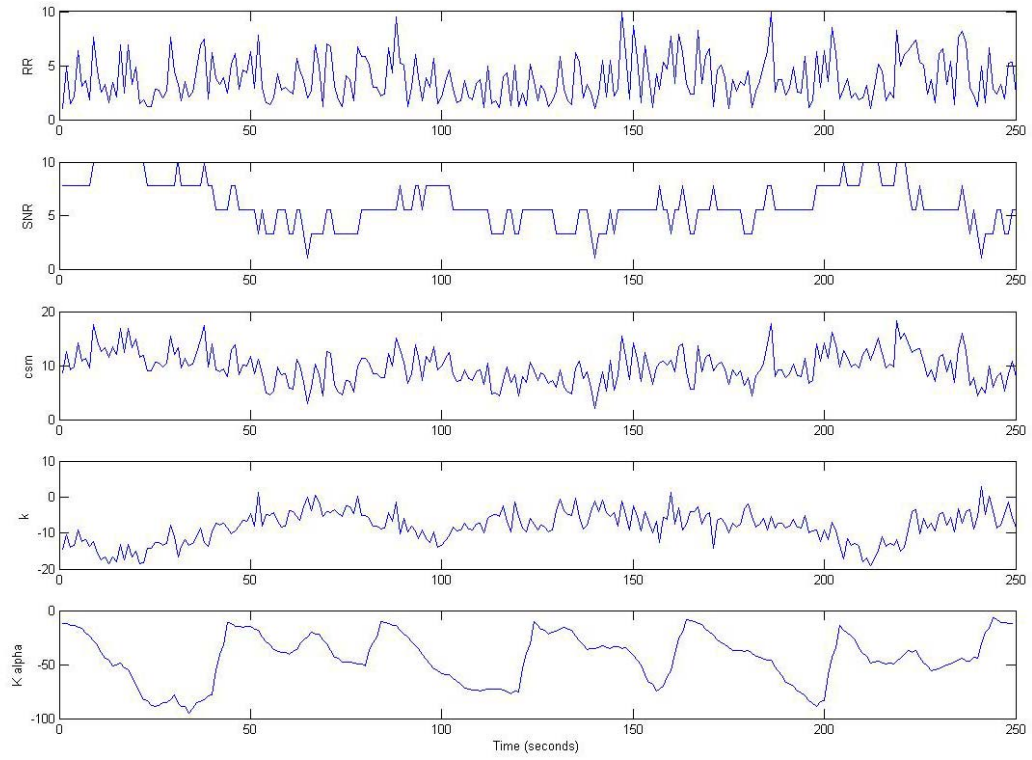

Figure 4: Normalised Input Signals, Intermediary Signals and Kα Output for SV26

The GPS data was also analysed using the software Leica QC. This was used to provide an independent measure of the multipath estimate for SV26. The Teqc software could not be used to compute the MP1 multipath estimate as it requires dual frequency data to compute this.

Figure 6 shows the Leica QC code multipath time series estimate. Some of the large multipath estimates (peaks >±1m) according to Figure 6 occur at approximates epochs 66, 75 93, 129, 159, 203, 219, 235 and 244. Comparing with the Kα in Figure 5 where the peaks occur at epochs 44, 66, 85, 124, 164, 204, 224, 236 and 244. It can be seen that the dDCA algorithm is able to identify the periods with a presence of large multipath to within about 8 seconds of its occurrence.

Taking a closer look at the Kα results:

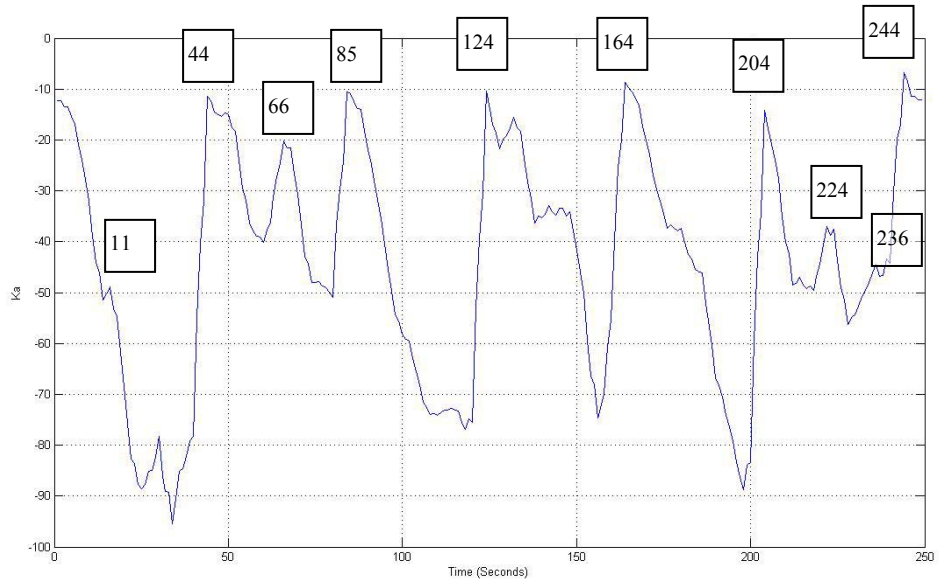

Figure 5: dDCA Kα Output for SV26 Time Series

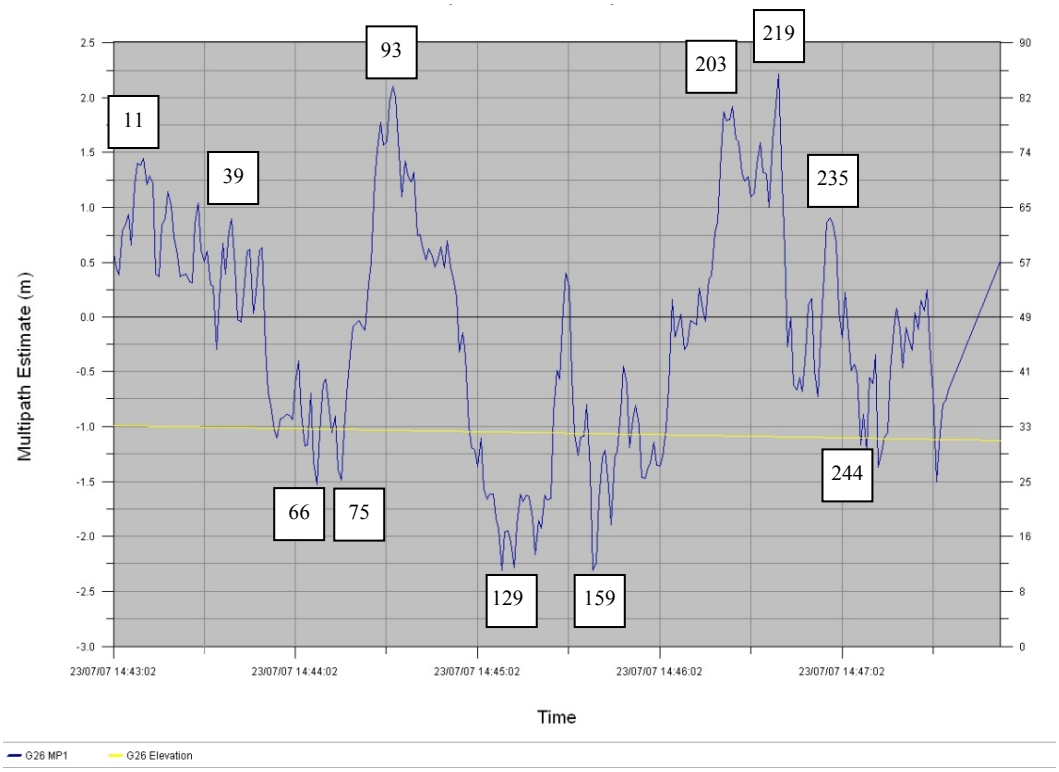

Figure 6: Leica QC Code Multipath Time Series Estimate for SV26

When analysing Figures 5 and 6, it is not expected that they appear identical but rather that the Kα time series would exhibit a high anomaly value (peak) when there are high values (both + and -) of the Leica QC multipath estimate shown in Figure 6.

4. CONCLUSION

The deterministic Dendritic Cell Algorithm appears to be able to identify multipath in a GPS time series for a static antenna data set. The linear min-max normalisation was simple and effective. Results using the Range Residual and the SNR for danger and safe signals respectively showed good results. The use of the RRs means that Double Differences do not need to be formed and so it can be used for stand-alone GPS, unlike Teqc's MP1 calculation which require dual frequency data. In addition, it does not require for the accurate position of the antenna to be known in order to compute the Kα anomaly values. Other tests have been conducted as part of this project using different inputs such as the Doppler residual and double difference residual for differential GPS.

Further work needs to be conducted to improve the tuning for number of antigens, lifespan/migration threshold, and other parameters within the dDCA. Further investigation also should include normalising smaller segments of the data set. Having a series bank of dDCA filters for large time series, as well as testing with kinematic GPS data.

The results from the dDCA can used to identify epochs affected by multipath and these values can be used as a weighting mechanism in a Kalman filter or other routine.

REFERENCES

Al-Hammadi, Y., Aickelin, U., and Greensmith, J., (2008), DCA for Detecting Bots. In Proceedings of the IEEE World Congress on Computational Intelligence (WCCI2008), page 1807-1816, Hong Kong 2008.

Andreotti, M.T., (2007), Global Navigation Satellite in Urban and Indoor Environments - A New Tool to Visualize, Understand and Use Multipath. PhD Thesis, University of Nottingham.

Bilich, A., and Larson, K.M., (2006), Mapping the GPS Multipath Environment Using the Signal-to-Noise Ratio (SNR). Radio Science, Vol.42, RS6003, doi10.1029/2007RS003652, 2007. American Geophysical Union.

Greensmith, J., (2007), The Dendritic Cell Algorithm. PhD Thesis, School of Computer Science, University Of Nottingham.

Greensmith, J. and Aickelin, U., (2008), The Deterministic Dendritic Cell Algorithm, 7th International Conference on Artificial Immune Systems (ICARIS 2008), pp 291-302, Phuket, Thailand, Springer LNCS 5132.

Greensmith, J., Aickelin, U., and Tedesco, G., (2008a), Information Fusion for Anomaly Detection with the DCA. Information Fusion, in print, 2008.

Greensmith, J., Twycross, J., and Aickelin, U., (2006), Dendritic Cells for Anomaly Detection. In Proc. of the Congress on Evolutionary Computation (CEC), pages 664–671, 2006.

Greensmith, J., Aickelin, U., and Feyereisl, J., (2008b), The DCA-SOMe Comparison: A Comparative Study Between Two Biologically-Inspired Algorithms. Evolutionary Intelligence: Special Issue on Artificial Immune Systems, accepted for publication.

Lutz, M. and Schuler, G., (2002), Immature, Semi-mature and Fully Mature Dendritic Cells: Which Signals Induce Tolerance or Immunity? Trends in Immunology, 23(9):991–1045, 2002.

Oates, R., Greensmith, J., Aickelin, U., Garibaldi, J., and Kendall, G., (2007), The Application of a Dendritic Cell Algorithm to a Robotic Classifier. In Proc. of the 6th International Conference on Artificial Immune Systems (ICARIS), LNCS 4628, pages 204–215, 2007.

Ogundipe, O., (2003), The Use of Real Time Kinematic GPS on Construction Plant. PhD Thesis, University of Nottingham.

Roberts, G.W., (1997), Real Time On-The-Fly Kinematic GPS. PhD Thesis, University of Nottingham.

BIOGRAPHICAL NOTES

Dr Oluropo Ogundipe is a Research Fellow at the IESSG, University of Nottingham. She has a Bachelor's degree in Surveying and Land Information from the University of the West Indies and a PhD in Engineering Surveying and Space Geodesy from the University of Nottingham. Her current research focus includes the Mapping of sub-surface utilities and the use of GPS for Bridge Monitoring, Her research interests include Network RTK GPS, sensor Integration, augmented reality and multipath mitigation. She is a graduate member of the UK's Chartered Institution of Civil Engineering Surveyors.

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