This document is to list all of the corrections requested from the viva on the 24th January 2015. The table below includes each correction ad verbatim from the document provided shortly after the viva and includes columns to highlight the work I have done to address them. Where possible, I have included the amended text (in italics) from the revised thesis. If this was not possible, then I have written a short paragraph on the changes made. The page and paragraph that the change can be found on is also listed, as is room for any comments that may be relevant.

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| --- | --- | --- | --- | --- | --- | --- | --- |
| Number | **Examiner's Comment** | **Page** | **Paragraph** | **Changes Made** |  |  | **Additional Comments** |
| 1 | Base line of WSN sending out all data to base station without DPs, i.e. a  simple mutlihop network that sends images directly out via the  shortest route and the base station does the classification. You may  want to consider the base station having MK in one scenario and  HK in another, i.e. two baselines. | 138 |  |  |  |  | Issues with the original simulation were discovered early on when changes were starting to be made to include all observations.  These included issues that were identified in the viva, such as parallel send and receive. The simulations were amended and all were re run. The time to run all scenarios again, as well as the 2 new central processing was great and was only completed 2 weeks before the due date of the amended thesis. |
| 2 | Rerun all experiments with the additional scenarios. You should report  the total number of images that were generated, the number that  arrived at the base station and the (ideally) number that were  dropped. | 138 |  |  |  |  | The stats show the results from as many runs as possible from each scenario which, in most cases, is 25.  Maybe plots are best grouped by scenario rather than by plot type? |
| 3 | Formalise the description of the experimental design clearly stating what  variables were kept constant and which were measured. The  simulation chapter needs to include (in addition to the verbal  explanation) more formal software documentation of the simulation  system, such as with appropriate UML diagramming methods and  maybe also pseudo-code. This includes making clear how particular  random generator parameters were set – i.e. where the values  came from and how used. | 138 |  | The simulations chapter has been rewritten to display the plots more clearly and explain the structure of the simulation in greater detail.  A table (7.2) has been added that details all of the parameters that are both static and confirgurable within the simulation. Individual parameters that require more explanation have been described in subsequent subsections.  Each scenario has been described, as well as how the network is saturated and how the transmission rate is varied. |  |  |  |
| 4 | Error bars on graphs, although box and whisker plots with the mean  indicated would be more appropriate | 150 |  |  |  |  | The standard error for the transmission time is very small, whereas the standard deviation can be huge. Therefore, showing error bars or box and whisker plots has proven to be difficult. Instead, scatter plots have been used that show a 95% CI with the mean being the central point. I hope this is OK! |
| 5 | Keep figures with the text that describe them | 150 |  | Using the float package, all plots have been set with the *H* setting to ensure that they are placed exactly where they are defined. |  |  |  |
| 6 | Remove claims about energy usage in the network | - |  | Claims about energy usage have been removed from both Chapter 7 and 8. |  |  |  |
| 7 | Separate out architecture design from scenarios of its use | 73,74  88 | Fig 4.4.  DB name removed | I have read through the walkthrough section of the architecture chapter and checked any points that describe the architecture design.  I have moved the EXIF section above walkthrough and removed mention of specific choices, such as MySQL, when talking about technologies that could be replaced. |  |  |  |
| 8 | Make it explicit that the DA will be running on a laptop/desktop computer | 66  124 | 3  1 | *Data aggregation nodes should not be hampered by limited battery life that deployed*  *nodes would experience as we expect them to be placed in a base station with power*  *availability and access to the Internet. Therefore, DA nodes would typically be desktop*  *computers with a constant power supply.*  *we combined the DP and DA nodes into one desktop stored at DGFC, that*  *contained both a Digimesh radio and an Internet connection* |  |  |  |
| 9 | State what your architecture is capable of doing that OGC-SWE is not,  particularly compared to deployments of OGC-SWE that have been  used for capturing animal images | 90 | 3 | *One of the key features of K-HAS is that it is not a static deployment. The knowledge that the network holds at the time of deployment will rarely be the same as*  *the knowledge held after a few months. Humans enrich the existing knowledge base*  *and the nodes are able to make inferences about the data they are sensing, improving*  *their classifications the longer they are deployed. When developing this architecture,*  *GSN was the most robust architecture of those that we researched and tested, the sup-*  *port for many databases, administrative interface, native support for many widely used*  *sensors meant that it was a better choice than a middleware that adopted the OGC SWE*  *standards, especially as we were not interacting with SWE systems in our motivating*  *scenario. However, while GSN is stable and mature, its large codebase does mean that*  *there are dated features, such as using SOAP instead of REST and an unintuitive web*  *interface that does not utilise web sockets. A middleware with similar automation on*  *receipt of sensor data could be used instead of GSN that did follow the standards set*  *out by the OGC. We believe that this should require few changes to the core K-HAS*  *architecture as it currently stands.* |  |  | I could not find explicit examples of OGC SWE implementations being used for animal tracking. The Sensor Anywhere project (SANY) was closest but any papers mentioned animal based networks in theory only. |
| 10 | Clarify role of image processing and use of templates. Bring this  discussion into Chapter 3 | 55/56  86/87 | 3/1,2,3 | *Triton is currently capable of processing a set of images and extracting the largest object of interest, if one is detected. The primary benefit of this is that it requires no*  *training initially and works, with fairly good accuracy, from the time of deployment.*  *However, functionality can be extended by storing the extracted images and associating it with the actual content, i.e. animal name, future extracted images can then*  *be matched to the templates, within a threshold, to assist with classifications within the network. Currently, the templates are extracted, stored and associated with their*  *contents once classified by a human, but Triton does not use these. If Triton detected*  *an interesting image, it could then search a folder of templates and use OpenCV to*  *compare the images and provide a cursory classification based on the closest match.*  *Extracted images are stored in black and white and are only a few kilobytes in size, this*  *will be useful as we expect that a large number of templates would be required in order*  *to accurately identify an object of interest. For example, in our motivating scenario, an*  *animal could be any distance from the camera, its legs could be in different positions or*  *its angle it faces towards the camera could be different, giving many possible images.*  *This process could be optimised by only matching regions between extracted images,*  *such as the head or body, but this would require further experimentation.*  *Our Triton program, described in Section 3.4.1 is run on the set of three images. These*  *images are converted to black and white and combined to build a background model*  *for the complete set. The detected background is then removed and the final image is*  *then searched for objects, where objects in the foreground will be shown with white*  *pixels. The largest object is then found in the image and extracted to create a template,*  *shown in Figure 4.10.*  *Processed images of previously sensed images are stored on the DP node and associated with the confirmed classification, confirmed by a human or a node. Although*  *the memory available on a DP node is typically around 32GB, this could easily fill*  *in a matter of months if 3 full HD images were stored for every observation. Storing*  *a single black and white template that contains a portion of the image is much more*  *efficient and can still easily be associated with the classification made. The extracted*  *image is then compared with the existing images, using the knowledge base to prioritise*  *templates for comparison. In this example, nocturnal animals are prioritised and especially nocturnal animals with active projects associated. If the DP node has received*  *an observation from the same DC node recently, then it will check for a classification*  *on that and check for a match there first.* |  |  |  |
| 11 | When explaining the image processing functionality make clear the  distinction between classifying an image as interesting or  uninteresting and classification in the sense of determining a  particular species. | 39  50  55  64  73  76  87 | 2  2  2  4  5  2  3 | I have looked at each instance the term classification has been used in the context of image processing and clarified whether it refers to species level or interesting vs empty observations.  ­. |  |  |  |
| 12 | Make a clear statement regarding what has actually been implemented  and is a part of the completed system as opposed to functionality  which you have experimented but not made operational – thus  explain that species classification has not been implemented in any  particularly effective way in the final system, but you can explain how it would be done. | 55  81  86 | 2  3  2 | Statements of this nature have been made throughout the thesis (where relevant) whenever a piece of the architecture that has not been implemented is mentioned, a statement serving as a disclaimer has been added. |  |  | This approach may seem repetitive and maybe it is best to boil this down to a single statement the first time it is mentioned? |
| 13 | With regard to classification with templates, how would templates be  matched if objects are at different angles, distance from the  camera, etc? | 55 | 2 | See point 11 for the explanation of templates. |  |  |  |
| 14 | Throughout the thesis make it clear whether functionality relies on image  classification to determine a species (that has not been  implemented) or identifying potentially interesting images |  |  |  |  |  |  |
| 15 | Provide link to Triton source repository | 50 | 2 (Reference 50) | Link to repository added in references. |  |  |  |
| 16 | Correctly use your definition for accuracy (page 56) | 52 |  | As we discussed in the viva, the calculation for accuracy was not right and not what was used in the subsequent tables.  I have redefine accuracy for both True Positive and True Negative images and referenced which ones have been used in the text. |  |  |  |
| 17 | Make clear that adding rules to Drools requires specialist knowledge of  the drools programming language | 79 | 2,3 | *In order to add rules to the Drools system, knowledge of the Drools syntax and, ideally, Java is required.*  *The functionality of Drools is extensive and the engine is very powerful, however, it does require specialist knowledge to use and manipulate rules. Using a custom developed Drools web interface , detailed in Section 4.3.3, we created a simplified interface that uses a custom REST API for Drools,* |  |  |  |
| 18 | Indicate the circumstances that could lead to a rule being added to  Drools – where has the required information / knowledge come  from? | 89 | 2 | *When a user classifies the observation, they see that a clouded leopard has been spotted in the same area on the same day for the past 5 weeks and they create a rule (in Drools syntax) to automatically classify images from this camera that have a similar time (within an hour) and have an object extracted from them by the image processing. The user can then upload the rules through the same web interface and it will instantly become active on the system. In the current implementation, rules can only be added by humans and the Drools API we have implemented then updates the rule base. The web interface allows users to study patterns in existing sensed data and perform queries on the database, from this they can identify rules and upload them.* |  |  |  |
| 19 | The description of the architecture needs to be accompanied by  software documentation diagrams or code (such as UML interaction  and activity diagrams and / or pseudo-code) that makes clear the  main components of the system (both software and human  interventions) and how they interact with each other. | 69  82 | Fig 4.2  Fig 4.9 | I have added a sequence diagram that explains how a packet is routed, which also highlights what has been implemented in the current system.  An activity diagram has also been included to show how the routing protocol configures the nodes. This figure has also been referenced in the simulations chapter. |  |  |  |
| 20 | SSN ontology is both sensor-centric and observation-centric. | 99 | 2 | SSN and SUMO (extended with SHO and SDO) have been moved to a separate section, entitled 'Combined Sensor and Observation Ontologies' |  |  |  |
| 21 | Introduce SUMO as a general purpose upper ontology (with appropriate  reference(s)). Then go on to state how it has been specialised for  sensor network deployments | 100 | 2 | *The Suggested Upper Merged Ontology (SUMO) is a general purpose ontology [83] that provides general-purpose terms and is intended to be extended for domain specific*  *ontologies. In [37], SUMO has been extended to link sensor hardware and sensor data*  *ontologies in order to assist with searching and evaluating distributed and heterogeneous sensor networks. The work combines the Sensor Hierarchy Ontology (SHO), the*  *Sensor Data Ontology (SDO) and the ability to ‘plug in’ extension ontologies.*  *The SHO describes the hardware of a sensor node, as well as its accuracy, transmission*  *medium and data processing capabilities. The SDO, however, describes the sensing*  *properties of a device beyond the hardware and the context of the sensor can be enriched with information about spatial and/or temporal observations. Similar to GSN*  *(Section 2.3.2), SUMO uses the notion of virtual sensors where a group of sensors can*  *be described together to provide abstract measurements. In [37], the example of a humidity sensor, temperature sensor and wind speed sensor being collectively described*  *as weather sensors. The SHO ontology is another extension of SUMO, from [37], that represents the hardware of a WSN, including the node itself, data transmission units, data processing units and individual sensors. The data model describes a sensor with metadata describing features such as measurement type, transmission range and physical properties.* |  |  |  |
| 22 | Remove claim that your ontology is modular. You reuse existing terms  by importing them, but it is not modular |  |  | All claims about modularity have been removed from the Introduction, Chapter 5 and Chapter 8. |  |  |  |
| 23 | Need a critical discussion as to why SSN does not meet your needs | 102 | 2 | SSN terms added to Table 5.4 and:  *We found that SSN, SensorML and Darwin Core satisfied many the hardware and*  *much of the sensed data subsections of K-HAS completely. We have used these exist-*  *ing ontologies to develop an aligning ontology that connects ontologies across multiple*  *domains to support our proposal of K-HAS, extending the concepts in existing ontologies with K-HAS specific concepts.*  *The SSN ontology is a modular ontology created by combining concepts from existing,*  *commonly used ontologies and allows for domain specific concepts to be imported.*  *Some of the main uses cases for the SSN ontology are provenance and data discovery,*  *which are also key within K-HAS. However, the tiered structure of K-HAS did not*  *map directly to SSN and it proved difficult to represent the flow of knowledge through*  *a network, as humans can also perform similar operations on observations and the observations are enriched as they pass through the network. However, while we did not*  *use the ontology directly, many of the concepts can be mapped directly (shown later in Table 5.4) and it would be possible to use import modules from SSN and extend*  *them with the concepts specific to K-HAS, SSN does not describe domain concepts*  *(such as time or location) as this is expected to be handled by imports from more spe-*  *cific ontologies. K-HAS allows humans to act as sensors, which would require slight*  *modifications to SSN, as well as extending with the ability to provide classifications*  *for sensed data.* |  |  | The referenced table may be too far down the chapter to be of any use? |
| 24 | Correct and move to appropriate part of the thesis, probably chapter 3. I would suggest removing the term global knowledge. | 58 | 1 | Moved to chapter 4 (as chapter 3 was primarily technical and the only fitting place I could see was after Danau girang was introduced) Removed references to global knowledge and only included an example of local knowledge |  |  |  |
| 25 | Combine the two graphs onto a single plot. | 46 | Fig 3.5 | Plots combined. |  |  |  |
| 26 | Separate out UK wet and dry and provide humidity values for the  experiment (if you have them). |  |  | I am afraid that I do not have these values. Although they could be retrieved retrospectively by using a weather based API? |  |  |  |
| 27 | Include the values for when DGFC loses signal |  |  | I am afraid I also do not have these values, I cannot find the files in the Dropbox folder that these experiments were stored in. |  |  |  |
| 28 | When stating that there are multiple tools, provide more than one  citation | 39  139 | 3  3 | Included multiple references when discussing image processing tools (OpenCV and CvBlob) and simulation tools (NS2 and MASON). |  |  |  |
| 29 | Remove the acronyms ‘LK’ and ‘GK’ and replace with their expanded  terms |  |  | All instance of LK and GK replaced and removed from the glossary |  |  |  |
| 30 | Don’t use the term scientific observation when you specifically mean an ecological observation |  |  | I have reviewed each use of the term scientific observation and replaced any terms that do not relate to OBOE or K-HAS with ecological observation. |  |  | This may need reviewing as I may have misunderstood what was wanted here. Please let me know if I have missed any! |
| 31 | Remove et al from references |  |  | All instances of 'et al' and 'and others' removed from the bib file as they were both formatted to output as 'et al'. |  |  |  |
| 32 | Provide a map of the location of the field centre in its wider context, i.e.  the part of the globe, in Chapter 1. Improve resolution of Fig 3.2  and highlight regions on picture. | 37 | Fig. 3.2 | The original figure has been replaced with a figure used by the researchers at the field as it is higher resolution and has key points labelled.  It has been moved to Chapter 1 but the image it replaced was at the highest resolution I could get and, as the new image seems to negate its need, I have removed it and referenced the figure again in Chapter 3. |  |  |  |
| 33 | Remove claim at end of §3.3.1 that, based on your experiment, you can  conclude that other experiments would give you the same results in  the UK and Malaysia | 47 |  | Claim removed. |  |  |  |
| 34 | Field names in Listing 4.3 for set.csv don’t match those given in Listing  4.4 | 72  73 |  | Field names were using the wrong Darwin Core archive listed in the wrong chapter, this has been corrected. |  |  |  |
| 35 | Turn the heading ‘Findings’ in §5.1.2 into the subheading §5.1.3 | 101 |  | This has now been changed to 5.1.4 |  |  |  |
| 36 | cite all the commercial cameras considered | 122  123 | 4  1 | There were very few commercial cameras that has wireless capabilities but I have included the other Reconyx camera we looked at and the thesis previously mentioned the Raspberry Pi camera module. |  |  |  |
| 37 | 6.1 provide a picture of the Buckeye cameras used with their case | 123 | Fig. 6.1 | Figure included at 6.1. |  |  |  |
| 38 | 6.2 State why you are only taking 2 pictures when up until this point  you have been working with 3 pictures | 126 | 1 | *This was fine for images of*  *humans but we found that triggers caused by animals could miss and have no content. We therefore changed the number of images to two so that network traffic was still minimised, especially as images could only be sent when power was available at the field centre.* |  |  |  |
| 39 | Listing 6.4 remove the setting of the scientific name as you are not sure  which of the two species it is | 131 | Listing 6.1 | Setting of species removed. |  |  |  |
| 40 | State how many rules were used in the LORIS deployment and an  indication of the accuracy of the system | 135 | 3 | Using the Weka package \cite{hall2009weka}, we initially constructed a J48 decision tree (an open source Java implementation of the C4.5 algorithm \cite{quinlan93}) but found that the accuracy was only 27\% and the rules extracted from the model related to individual times that had only seen a single observation. From this, we then used a decision table \cite{Kohavi1995} within Weka that created a model yielding an accuracy of 53\%. We used the resulting model to extract a collection of 281 rules that could be run on a DC node. Figure \ref{imp:lst:rule1} shows a rule that was created from the output. This rule checks the time of capture for the observation, the temperature and the moonphase; which has been converted into a numeric value. If the temperature is fewer than 26 degrees and the time is between 3pm and midnight, then there is a 25\% chance of the species classification being a goat. The if-statements are executed in order and the classification that matches the properties of the observation, and has the highest percentage chance, is forwarded to a DP node.  With Weka, we experienced the same problem as with SQL, we only had 2700 classifications made by people with domain knowledge, so any models generated from Weka were limited not just to those species in those classifications, but to those species with a sufficient number of observations. Of those 2700 classifications, there were only 45 different species and some had fewer than 10 sightings. For example, the set we used primarily contains goats and the resulting model provided 84\% accuracy when given an observation of a goat. However, the Malay badger had very few sightings in the set and the model only yielded 17\% accuracy. With future work, we would like to add new classifications to this model and test it extensively with new, unclassified data, as well as add more variables on top of moonphase, temperature, date and time but ensuring they are variables that would be available to data collection nodes.    Because the features used to generate the rules are available in every observation, and do not require any external information, DC nodes are able to process the series of if-statements quickly. This method of knowledge-processing comes at the cost of accuracy, when compared to using existing data, image processing and/or a dynamic knowledge base, but the speed and simplicity of these rules mean that they can be used by almost any node, regardless of computational capability. |  |  |  |
| 41 | Indicate which part of the interview in appendix E is shown in appendix  F | 133 | 1 | I have changed the interviews to be from the same person (originally they were 2 different researchers) and indicated where they correspond. |  |  | Would you want this to be specific to allow the reader to match up the excerpt? |
| 42 | p126 rewrite paragraph about global knowledge and local knowledge of  clouded leopard sleeping patterns | 133 |  | *These face to face sessions gave us insight into patterns and observations that researchers had learnt during their months, or years, at Danau Girang; something we would have otherwise been unable to learn in our short periods at the field centre. An example of this is learning that the clouded leopard is not nocturnal around Danau Girang, while it is in the rest of the world. It is common knowledge that clouded leopards are nocturnal animals but they have been seen at all hours of the day around DG. Researchers believe that this could be due to the fact that the rainforest is secondary, growing back after heavy logging 40 years ago, or human impact from palm oil plantations that border the edges of the rainforest or the availability of prey. Whilst the local knowledge that clouded leopards can be seen throughout the day cannot be directly encoded as a rule, it does mean that the animal can be removed from rules that may filter out nocturnal animals as possible classifications for images captured during the day. While we were not able to construct a full set of rules from these findings, the results*  *have provided support for patterns extracted from existing data that has been classified by researchers, which we discuss further in the next section.* |  |  | I could not fully remember if this was to be rewritten as it was too complex or (as Alun has suggested) to remove the global knowledge reference. I have rewritten it as both in case, but I welcome feedback here. |
| 43 | Citations for Weka and J48 | 135 | 3 |  |  |  |  |
| 44 | Clarify 400 hour claim on p158 (the new simulation experiments will give  you a proper value for this against the baseline when there is no  intelligence in the network) | 162 | 3 | In Chapter 7, we explain the implementation and results of our simulations to model an ideal deployment of K-HAS. We model every variable of the network on existing data collected from our motivating scenario and show that the delivery of interesting observations can be effectively halved from almost 120 hours (for central and no processing) down to 64 hours for HK-HK-NK or 80 hours for K-HAS.  % hours by more than four hundred hours, when compared to the current manual solution.  We also outline how the network is able to prioritise data that it believes to be interesting, using a priority queue mechanism that delays data it believes to be empty. |  |  |  |
| 45 | Typos/Minor Corrections |  |  | All addressed |  |  |  |