

K-HAS: An Architecture for Using Local and Global Knowledge in Wireless Sensor Networks

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ABSTRACT

Sensor networks are driven by the activities of their deployed environment and they have the potential to use data that has previously been sensed in order to classify current sensed data. In this paper, we propose the Knowledge-Based Hierarchical Architecture for Sensing (K-HAS), an architecture for Wireless Sensor Networks (WSNs) that uses different tiers within a network to classify sensed data. K-HAS uses three tiers for in-network classification: the lower tier actively senses the data and packages it with relevant metadata, the middle tier processes the data using a knowledge base of previously classified sensed data and the the upper tier provides storage for all data, a global overview of the network and allows users to access, and modify classifications in order to improve future classifications. Initial experiments on the performance of the individual components of K-HAS have proven successful and a prototype network is planned for deployment in the Kinabatangan Wildlife Sanctuary, Malaysia.

1. INTRODUCTION

Wireless sensor networks (WSNs) allow for wireless communications between embedded devices that can be deployed for long periods in harsh environments. Because of their flexibility, WSNs are applicable to a wide variety of domains and a lot of research has been done to determine the best topology for a network, or the best routing protocol. Much of this research is aimed to solve a specific problem and can be difficult to translate to other scenarios.

There is already substantial research on the the various routing protocols that have been developed for WSNs. [3] and [2] survey routing protocols highlighting the constraints of deploying a WSN, such as battery life, transmission medium

or coverage, and how each protocol addresses changes in the topology of a network as well as aiming to be as energy efficient as possible.

In this paper, we explore the higher level architecture of a sensor network and propose the Knowledge Based Hierarchical Architecture for Sensing (K-HAS), an architecture designed to utilise the knowledge related to its environment in order to classify sensed data. We define sensed data as data that originates from a node that is related to what that node has been tasked to sense.

There has been research into sensor networks that use context-awareness in order to improve the quality of the sensed data, as well as the lifetime of the network. In [23], sensors have been used to monitor the movements of patients and adapt their power usage based on the behaviour of the patient.

K-HAS aims to extend context-awareness in order to use the knowledge of its environment to classify the sensed data. We call a sensor's knowledge of its environment *local knowledge*, which we define as: knowledge of an area that can be gained from experience or experiments within that area [8]. An example of local knowledge is: a biologist knowing that a particular species is only active in a certain area of an otherwise uninhabited forest. If this knowledge is encoded onto a sensor then that node could preliminarily classify that data before it reaches the base station. We present our prototype network as a vision-based WSN but the design of K-HAS is such that it is suited to any type of WSN.

The rest of this paper is structured as follows: Section 2 provides an overview of our testbed for K-HAS. Section 3 describes the design principles and background research. Section 4 introduces the K-HAS architecture. Section 5 highlights an example scenario for K-HAS and Section 6 provides a preliminary evaluation of our architecture. Section 7 covers some of the related work while Section 8 concludes our findings and highlights any future work.

2. DANAU GIRANG RESEARCH AREA

Cardiff University's School of Biosciences is working with the Malaysian Sabah Wildlife Department to provide a field centre, called Danau Girang, within the Lower Kinabatangan Wildlife Sanctuary, shown in Figure 1. Danau Girang is used by researchers at Cardiff University, as well as other institutions.

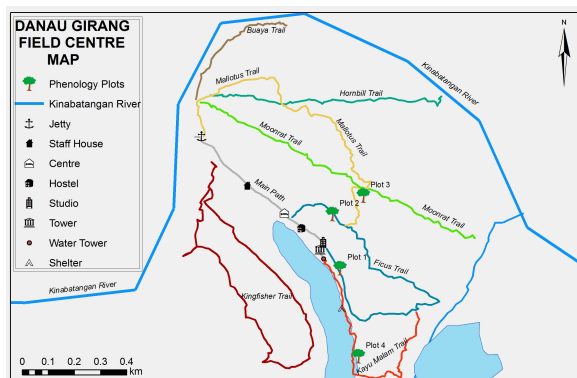


Figure 1: Map of Danau Girang Field Centre

There are long term PhD students that stay in the field centre for extended periods and shorter term Masters schemes that allow for projects that last around 6 months. Danau Girang also offers field courses that allow students to experience practical field work and carry out small research projects.

22 motion-sensitive wildlife cameras have been set up along the Kinabatangan River, as well as up to 1km deep into the forest, for the Kinabatangan Carnivore Programme which aims to look at the presence of carnivores in a corridor of forest between the Kinabatangan River and palm oil plantations, as well as an isolated lot of forest. The images from these cameras are used in a variety of the research that is undertaken at Danau Girang.

The cameras are triggered by infrared sensors and images are then stored on a memory card. Students at the field centre then go out to one half of the deployed cameras every 2 weeks in order to change the batteries and retrieve the SD cards. Because of the large area that the cameras are in, it is not feasible to collect the SD cards of all the cameras in one day, so the task is split into two. Images are transferred onto a netbook and processed manually, by the students.

When cameras are first deployed they are able to last for more than four weeks on a single charge but the humidity does affect the battery life within a short period of time and this is reduced to around two weeks. This could be due to the fact that the internals of the camera are exposed every two weeks and that the charging method for the batteries is not efficient, as it is limited by the fact that the field centre does not provide 24 hour power.

Due to the dynamic nature of the rainforest the cameras can be triggered often. The majority of the pictures taken are 'false triggers'. We define false triggers as movement, not caused by wildlife, that triggers the motion sensor in

a camera. This can be caused by the movement of the sun throughout the day, reflections on water or insects inside the camera.

In a period of 2 weeks more than 1,000 images can be taken, in extreme cases. Manually collecting and processing the images taken is time consuming for the researchers and affects research projects. Figure 2 shows the main building at Danau Girang, where images that have been collected from cameras are stored on a netbook, into folders sorted by the camera. These are then processed by research students in the computer labs in the building. This involves manually looking at each image and extracting images that are relevant to projects ongoing at Danau Girang. A single camera can yield more than 300 images in a space of two weeks, depending on activity in its location. The volume of images that need to be processed is a complex task for a researcher to accomplish, making it easy to miss some important images. It is also difficult for researchers to be aware of all projects at Danau Girang.



Figure 2: The Main Building at Danau Girang

Investigators in projects at Danau Girang often require images from the camera traps and it is currently a lengthy process to provide them. When a request is made by a third party, a USB drive is bought in the nearby town of Sandakan and returned to Danau Girang. The drive is then loaded with the relevant images and put on a coach to return it to Sandakan, where it is posted to the requester. This process can take weeks and is clearly not the most efficient way to share a large number of images.

K-HAS has been developed in order to automate the collection and processing of sensed data, using the local knowledge of the environment where the network is deployed to aid automatic classification. Danau Girang is the testbed for the viability of this architecture.

3. DESIGN AND BACKGROUND

WSNs have constraints such as: power availability, storage, transmission range and processing capabilities [22], and the design of a network needs to consider these constraints when selecting the nodes suitable for the intended purpose.

When researching the choice of nodes for a test deployment in Danau Girang, we encountered several limitations that restrict our options for hardware, and the communication

protocols. Thick vegetation in the rainforest causes significant signal loss (Section 6.2) and means that traditional communication protocols, such as Wi-Fi, prove to be unsuitable. A study in [7] showed that sensors deployed in the rainforest can experience signal loss of up to 78% when using Wi-Fi as the communication medium.

Thick vegetation and the rainforest canopy do not just affect wireless transmissions; the amount of sunlight that reaches the rainforest floor is also limited. This means that solar panels are unable to provide a constant source of power, limiting us to sensors that are capable of running, without maintenance, on battery power for a significant amount of time.

From our research, we discovered large variations between the features available on sensor nodes. Some are designed to last for long periods on a single charge, but have very little processing power, such as SunSpot nodes [20]. Other sensors are capable of running desktop grade software but are limited to battery life of only a few hours, for example the IGEPv2 [18].

Such large variations in nodes make some more suited to particular WSN deployments than others. From this, we have identified three categories of nodes. A node can be classified based on its processing capabilities and is thus suitable for WSNs with different purposes.

To classify these nodes, we must first present the definitions of data and metadata. In [4] data is defined as the illustration of information in a formally organised way to be interpreted and processed in order to accomplish computing tasks, such as an image. Subsequently, [6] defines metadata as ‘data about data’ or, more generally, metadata can be thought of as providing context for data, such as image properties (size, date created etc.).

The categories that we have defined are focused toward knowledge-based processing capabilities and are shown below:

- **Data Collection Nodes:** These are nodes with a static knowledge base, encoded at the time of deployment. The knowledge base holds information relevant to itself, such as: projects it is involved in, the direction it is facing and its location.

A Data Collection Node does not process the data that it senses but it can package sensed data with information from its own knowledge base and any metadata that is of note, such as the time the image was taken.

Upon receiving sensed data from its attached sensors, a Data Collection node packages the data and forwards that information to its specified Data Processing node, known as its *master*. Data Collection nodes are also responsible for routing data collected by other Data Collection nodes to their specified *masters*. If the master node is unavailable, then it is sent to the next Data Processing node that is available.

- **Data Processing Nodes:** Data Processing nodes act as an interface between Data Aggregation nodes and

Data Collection nodes. They contain a dynamic, partially global knowledge base. The knowledge base on Data Processing nodes consists of all the knowledge pertaining to the area of the network that it serves, such as: the number of nodes deployed in the area, all classifications made and the classified data itself.

Each Data Processing node serves a subset of the network and is responsible for processing the data to provide a classification. In our prototype, a classification is of images, but classifications can be made for any sensed data. The metadata is used to attempt an initial classification, if this does not prove to be successful then the data itself is processed. Processing the data itself is resource heavy and slower than using the metadata for a classification, so it is performed only if the data cannot be classified by other means.

The results of the classifications are stored on the node and used in future classifications. Processed data, and the original data, is forwarded to the Data Aggregation node. If a user changes the classification on the Data Aggregation node, this change is mirrored to the respective Data Processing node. Only classifications are stored on the node and all other data is forwarded to the Data Aggregation node.

- **Data Aggregation Nodes:** Data Aggregation nodes are responsible for storing all sensed data and their associated classifications. A global overview of the network is stored in a dynamic knowledge base, containing information such as: all classifications made, the location of all deployed nodes and the time period since sensed data was last received. Acting as a gateway to the network, humans use these nodes to view sensed data and modify the classifications.

These nodes process data with human interaction and are responsible for the most accurate classifications of sensed data, using the knowledge of the user and global knowledge to make more informed classifications. In a typical WSN, only one Data Aggregation node is required, acting as the base station.

4. K-HAS ARCHITECTURE

K-HAS is split into three tiers, each tier has different responsibilities for handling sensed data. Figure 3 outlines the design for our architecture. The arrows depict the flow of knowledge to and from the nodes, with the lower tier only holding static knowledge bases, this means that their knowledge bases are not updated when the node is deployed but the information held in their knowledge base can be used to update the knowledge base of nodes in the middle tier. The number of nodes shown are not fixed and, for example: a network that implements K-HAS can have multiple Data Aggregation nodes, or a single Data Processing node.

The upper tier contains the Data Aggregation nodes and the sensor middleware, responsible for aggregating all sensed data from the network and holding all knowledge related to the network. The middle tier consists of Data Processing nodes. Sensors route data to the middle tier for classification. This process requires local knowledge in order to assist with the classification of sensed data. The lower tier are the Data Collection nodes, tasked with routing the sensed data

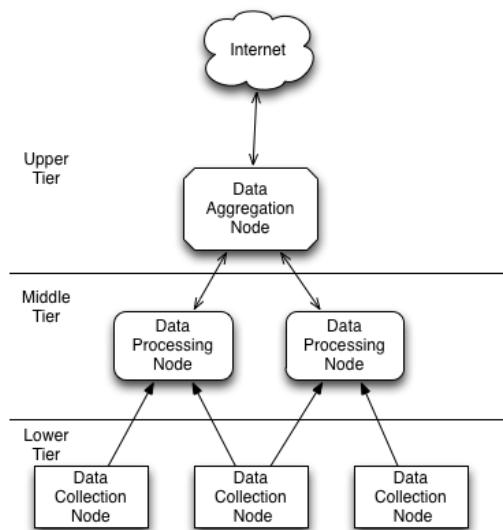


Figure 3: High level architecture for K-HAS

to the middle tier and acting as intermediate storage. These tiers are explained in greater detail below.

4.1 Lower Tier - Sensing

The lower tier of the network consists of Data Collection nodes. These nodes are primarily tasked with sensing their environment, but also with routing the sensed to the middle tier, as well as basic preprocessing of sensed data, through the use of file metadata, such as creation time and size.

These nodes have extremely basic processing power and limited storage so they are only capable of reading basic file metadata and sending files. Due to the reduced capabilities, Data Collection nodes do benefit from long battery life and they can run uninterrupted for several months at a time.

Data Collection nodes contain a static knowledge base that is encoded onto the node at the time it is deployed. The knowledge base contains basic information, such as: the area the sensor is deployed, common activity in that area, projects that the sensor is involved with and times that they may be most active. With the extracted knowledge from the knowledge base, it is possible to attempt to classify the data; although this step is not required, it can help streamline the classification process in the middle tier.

4.2 Middle Tier - Processing

The middle tier acts as an interface between the lower sensing tier and the upper tier, consisting of Data Processing nodes. The nodes in this tier act as sinks, receiving all data from sensors and processing it before it is sent to the base station. This reduces the flow of raw data to the upper tier and allows users to ‘subscribe’ to specific classifications of sensed data. For example: a biologist within Danau Girang could subscribe to custom alerts for pictures of crocodiles, while a lecturer at Cardiff University could subscribe to email updates for pictures of all carnivores.

The middle tier requires a dynamic knowledge base that is updated by both the base station and the Data Processing node(s). Nodes used in the processing tier are capable of sensing their environment but are tasked with the primary purpose of processing sensed data.

Images taken by digital devices contain additional metadata, known as: ExChangeable Image Format (EXIF) tags. These tags contain extra information about the image, for example: exposure time, compression, moon phase and GPS data (if available). Different camera models use different EXIF tags but tags are interchangeable and can be read universally.

```

File Name       : IMG_0001.JPG
Directory      : .
File Size      : 402 kB
File Modification Date/Time : 2010:12:22 16:35:10+00:00
File Type      : JPEG
MIME Type      : image/jpeg
Exif Byte Order : Little-endian (Intel, II)
Resolution Unit : inches
Y Cb Cr Positioning : Co-sited
Exif Version   : 0220
Components Configuration : Y, Cb, Cr, -
Flashpix Version : 0100
Color Space    : sRGB
Exif Image Width : 1920
Exif Image Height : 1080
ISO           : 800
Exposure Time : 1/30
Maker Note Version : 0xf101
Firmware Version : 3.0.1
Firmware Date : 2010:05:18
Trigger Mode : Motion Detection
Sequence     : 1 of 3
  
```

Figure 4: EXIF tags from a Reconyx Wildlife Camera

Figure 4 shows the output from the wildlife cameras used at Danau Girang, containing more information than some other cameras provide. EXIF tags allows for local and global knowledge to be combined in order to classify an image. For example, the moon phase is global knowledge but, coupled with the local knowledge of the direction that the source camera is facing and what animals would be active in that area of the rainforest at that time of the month, a Data Processing node would be able to classify the image without any image processing, or narrow down the possibilities of what the image may contain. If a classification cannot be gained from the metadata of the image, or previous classifications from the same camera, then image processing techniques are applied to the image. The cameras used at Danau Girang are motion sensitive and take 3 images, milliseconds apart, upon each trigger. If a match cannot be made, the set of images, as well as the extracted region of interest (ROI) is sent to the base station to be classified by a professional. In the worst case: that EXIF tags nor image processing can classify the image, then the image is marked as empty and sent to the base station as a false trigger.

Due to high processing demand, large amounts of sensed data and the use of software in multiple programming languages, a Data Aggregation node is used. The biggest limitation is the power consumption so nodes in the middle tier require a consistent power source such as solar power. Although the rainforest canopy has been mentioned as a limitation, the placement of nodes in the middle tier are not restricted to the location of cameras, thus allowing them to be placed in areas of direct sunlight.

4.3 Upper Tier - Aggregation and Access

The Data Aggregation nodes provide a gateway to the WSN through the internet, allowing global access. Most important is the need to store all sensed data, along with any classification metadata. One of our primary goals for the upper tier is to use software that requires no technical knowledge to use but allows an administrative overview, as well as the ability to dynamically adapt to changes in the network. Users with different requirements in the network can subscribe to particular streams of sensed data, such as images of carnivores or images of crocodiles in a defined region, and they are alerted via their chosen method, e.g. email. The Data Aggregation node allows users to view all sensed data from all deployed nodes, and their associated classifications. A global knowledge base is also held that stores information such as: the period that all the nodes have been deployed, the location of all nodes and any classifications that users have subscribed to be alerted about.

A local web server is used on the Data Aggregation node to allow multiple concurrent connections. The server provides access to all sensed data as well as the location of all deployed nodes and any knowledge pertaining to the nodes, for example, a node that has not sent any images for three days could be marked with a warning symbol as it may have run out of battery or filled its memory card. When data is received that does not have a classification, users can classify the data and the classification is mirrored back to the respective Data Processing node in the middle tier. This allows the user's classification to be used when similar sensed data is processed.

If a user's classification conflicts with the classifications made by Data Processing nodes then the node's classification is stored but the user's classification is used. This is because we believe that the knowledge of experts in the domain that a WSN is tasked to sense is more accurate than the sensors knowledge. When a user modifies a classification, the change is made on: the base station's database, all Data Processing nodes. These updates allow the classifier, used primarily on the Data Processing nodes, to learn from previous classifications and make more informed classifications in the future.

Each Data Aggregation node would typically be used as a Base Station and, as such, we would expect more powerful hardware to be used that would not provide limited storage. However, Data Aggregation nodes also provide the option to mirror their database to an external online service that is relevant to the sensed data, for example our prototype network is image-based so we use Flickr [16]. This is beneficial for networks that may not always have internet access or to provide external access to users that may not be based where the network is deployed, such as part-time researchers.

Although many comparisons can be made between a Base Station and a Data Aggregation node, such as providing a local store for all sensed data and allowing an administrative overview of the whole network. However, multiple Data Aggregation nodes does not mean that they will all hold the same data, as they can each be used for different purposes. For example, using Danau Girang as an example, if two Data Aggregation nodes are used then one could be used for im-

ages that have been classified with hunters in and the other would hold all other data.

4.4 Network Topology

K-HAS has been designed to be used in a hybrid tree mesh topology. Data Collection nodes and Data Processing nodes form a mesh network relative to the locations of the deployed cameras, with the tree topology formed by the Data Processing node(s). In our prototype deployment, every Data Collection node is connected directly to a camera and a set of images is routed through the Data Collection nodes to a single Data Processing node (Section 3). Data Processing nodes are tasked with serving a particular region of the network and they build a knowledge base for that subset. Data Processing nodes are connected to the Data Aggregation node via a Wi-Fi connection and the Data Aggregation node is connected to the internet through Danau Girang's satellite internet connection.

In our prototype, the upper tier's internet connection allows for sensed data to be uploaded, for external access when the base station may not have connectivity, as well as serving as a remote backup. In our scenario, this provides the ability for researchers to work remotely, being alerted when images meet a predefined classification while not requiring researchers to be resident at Danau Girang. There is also the benefit of using the expert knowledge of these external researchers, rather than relying on the researchers at Danau Girang to confirm the classifications of the hundreds of images received each week.

5. EXAMPLE SCENARIO

To illustrate how the prototype functions, we describe a walkthrough of our prototype network in action, outlining the process undertaken when an image is taken at a camera to the image reaching the base station.

5.1 Sensing

A macaque moves in front of Camera 3, deployed 500m inland from the Kinabatangan River and triggers the motion sensor. A burst of three images are taken and saved to the SD card. The Data Collection node attached to the camera detects the images on the SD card and adds metadata to the image. Data Collection nodes hold a static knowledge base, created at the time of deployment, containing information relevant to its tasked purpose.

The knowledge base on the triggered Data Collection node denotes that the projects it is involved with are the detection of crocodiles and the detection of carnivores along forest corridors. It is also encoded that it is facing the river, as well as what its latitude and longitude are. This metadata is added to the three images and routed through the network to the middle tier.

5.2 Processing

The set of images and metadata are received by the Data Processing node and the EXIF tags of the image are inspected. Figure 4 shows how the EXIF data for the image may look. Using these tags and knowledge about the previous classifications from Camera 3 a classification is attempted.



Figure 5: Original image taken by a Reconyx Wildlife Camera in Danau Girang



Figure 6: Image with background removed and largest ROI extracted

Camera 3's past 15 images have been false triggers and the EXIF tags only show that the image was taken during the day, so the moon phase is not relevant. Because the images cannot be classified through the metadata, they need to be processed. The Data Processing node builds a background model from the 3 images and attempts to detect relevant objects in the foreground, the first image in the set, unprocessed, looks like Figure 5.

We use a computer vision package, called the Open Source Computer Vision library (OpenCV) [19], to build a background model from the images taken by that camera and attempt to identify objects in the foreground. These are then extracted and the largest ROI is used as the image contents. The ROI is compared with previously classified ROIs stored on the node and a match is made where possible. The largest ROI is saved separately, shown in Figure 6, and the metadata that originated from Camera 3 is then checked. The metadata shows that Camera 3 is tasked with the detection of carnivores so the Data Processing node searches the database of previous classifications for ROIs that match the ROI extracted from the image set.

An exact match is not found but a match is found similar to that of the flat-headed cat. The set of images, metadata and

the extracted ROI are classified as a flat-headed cat and sent to the upper tier. The ROI is saved to the Data Processing node, with the associated classification.

5.3 Base Station

In our prototype network, we are using a sensor middleware, called Global Sensor Networks (GSN) [1], that abstracts the physical connection of all sensors through the use of 'virtual sensors'. GSN is a java based, open source middleware that is designed to simplify the control of a heterogeneous sensor network. When new sensors are added to the network, as long as the underlying support is in the middleware, the sensor can be added using an XML file.

```
<virtual-sensor name="imagelistener" priority="10">
  <processing-class>
    <class-name>gsn.vsensor.BridgeVirtualSensor</
class-name>
    <init-params />
    <output-structure>
      <field name="taken" type="bigint"/>
      <field name="size" type="bigint" />
      <field name="image_location"
type="varchar(100)"/>
    </output-structure>
  </processing-class>
  <description>This virtual sensor reads images from a
local folder</description>
  <life-cycle pool-size="10" />
  <addressing/>
...|
```

Figure 7: Example of a Virtual Sensor XML file

Figure 7 shows an example file of a virtual sensor in GSN that periodically polls a directory for images matching a specified file mask; the processing class defines the class used to process the received data and the output structure explains the structure of the data, in this case: a string and two integers. From this, a sampling rate is set and the directory to monitor is added. All of the actual code used is abstracted from the user but easily accessible. To perform any of the processing, the Java classes, defined in the XML file, are used and can be modified. The data that is received in the specified structure is saved into a table, of the same name as the virtual sensor.

GSN comes with support for a wide variety of sensors and any that are not supported can be added through the Java classes. A Java web server with a google maps based interface to show all deployed nodes and the most recent sensed data. Users can also access and download data from one sensor, or many sensors that match a specified query. GSN, running on the Data Aggregation node, receives the images from the Data Processing node through the virtual stream of Camera 3. The images are saved to the database and researchers that have subscribed to images of flat-headed cats are notified.

Researchers then access the base station and inspect the received images, choosing to reject or accept the classification. In this case the researcher would see Figure 6 and it would be clear that the classification is incorrect. The researcher corrects the classification to a macaque and this would be changed within GSN's database. When internet access is available the sensed data stored on the base station, is mirrored to an online image sharing service in order to allow

users, who do not have direct access to the WSN, to view and classify data. In our network, the data is viewable by all but only approved users are able to modify any of the data. Changes made on the photo sharing service are also mirrored back to the base station.

Once a researcher has confirmed, or updated, a classification, and when the base station has internet access, the images are then uploaded to allow global access, with the new classification. The change is then mirrored to the Data Processing nodes, updating their database with the new classification. When a Data Processing node receives a similar image, the node compares it with the ROI and classifies it as a macaque.

6. ARCHITECTURE EVALUATION

The experiments in this section have been run to show the viability of the tiers within the K-HAS architecture, as well as the network topology itself. They have been run using the hybrid tree/mesh architecture, explained in Section 4.4 as this is the topology used in Danau Girang.

6.1 Sensed Data Processing

During a typical three month deployment along the Kinabatangan River more than 40,000 images can be taken. A large proportion of these images can be classed as false triggers.

Section 4.2 explains that, using OpenCV, we have implemented a programme that evaluated images taken by the wildlife cameras, between the period of November 2010 and March 2011. During this time 40,123 images were taken. Using the images, taken in sets of 3, and separating the images taken by specific cameras, we build a Gaussian background model and used that to detect animals in the foreground, classifying the detected foreground as the ROI, and extracting it.

As mentioned in Section 5, Figure 5 shows an image taken by a wildlife camera. The dynamic background and light levels should be noted here. This image is number 1, in a set of 3, a background model is built from these images and added to the pre-existing background model built by that camera. The foreground of the image is then extracted and ROIs, larger than a threshold, are identified. The largest ROI is then extracted from the image and saved separately.

From our visit to Danau Girang in June 2011, we collected images from two different three month deployments, in two different lots in Danau Girang, giving us just over 70,000 of images to test our approach. The images are sorted by the camera and the date of collection. We process every 3 images as one set, building a background model of all three images.

We manually process all of the images initially, marking images that are empty as false triggers. We then process the images, using our application, and a resulting processed image is created from every set of 3 images. If nothing is detected in a set then no image is created and that set is logged as empty.

There are four classifications that can be made with images sets:

True positive: An ROI is extracted that contains the animal in the set.

False positive: An ROI is extracted that contains nothing of interest.

True negative: A false trigger is correctly identified and no ROI is extracted.

False negative: An image with interesting contents is classified as a false trigger and no ROI is extracted.

The processed images are then compared with our manual findings. The accuracy of our application is calculated by the following equation:

$$Accuracy = (T_p + T_n)/TotalSets \quad (1)$$

Where T_p is the number of true positive sets extracted and T_n is the number of true negative sets.

Table 1 shows experiments run on a camera deployed in Danau Girang for a three month deployment, our initial run was on a subset of 879 images, or 293 sets, taken over the course of three weeks. Out of the 293 sets, we have extracted 54 sets that were *true positives* and 38 *false negatives*. This means that in this subset 92 images were of interest and 54 were classified correctly. If we were simply evaluating how effective our approach is at detecting interesting images in this set, we would get an accuracy of 58%. However, 199 *true negatives* were correctly identified and only 2 sets had an ROI extracted when there was nothing interesting in the set. This gives us an accuracy of 86%.

These preliminary results show that our method is effective at detecting false positives but is less effective at detecting false negatives. It appears that these misclassifications primarily come from black and white images taken at night, images where minimal movement of the animal has caused a trigger and images where an animal has caused a trigger but it has been too fast moving to be in the second two images.

After a longer deployment, we would be able to build up a more substantial background model to account for some of the animals being less dynamic in images and we expect this to decrease our error rate thus reducing the number of false negatives. While false negatives do mean that an image with interesting contents is missed, these should be expected in the initial runnings of our approach. Data Processing nodes send all the data of an image set to the Data Aggregation node, all three initial images and the classification (if any), and the input of researchers

6.2 Range of Wi-Fi

Studies have been done on how vegetation and humidity can affect the performance of wireless signals in the rainforest. In [7], tests in dense rain-forests have shown signal degradation of up to 78%, in wireless transceivers using the 2.4GHz frequency band. In order to test for ourselves, we ran experiments on the impact of forest environments on 802.11g Wi-Fi, in the UK and Malaysia.

True Positive	True Negative	False Positive	False Negative	Total Image Sets	Accuracy %
54	199	2	38	293	86.34

Table 1: Table Name

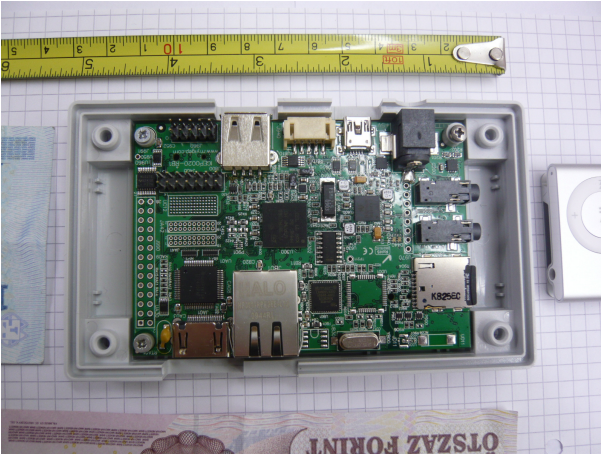


Figure 8: IGEP v2 Data Processing Node

In our initial evaluations of K-HAS, we used Wi-Fi as the communication medium between nodes because of its high data rate and interoperability with other devices. Our prototype implementation uses an IGEP v2 sensor, shown in Figure 8, categorised as a Data Processing node with a 1GHz single core ARM processor, 512MB RAM and Wi-Fi connectivity. Again, solar power is required to ensure these boards can run uninterrupted but they could remain active for just under a day on battery power. These nodes are running a lightweight Linux operating system, designed for the ARM architecture.

The IGEP nodes we used did not have any additional hardware and the nodes were tested without the use of an external antenna. A Java application was written to periodically scan for available networks and store those results in a text file. One IGEP board was set as the base station and attached to a tree, at the same height it would be if it was attached to a camera, and another was walked to specified points around the base station at defined locations. These locations were chosen to include as many distances as possible and as many different forms of obstacle between the searching node and the base station, such as: line of sight (LOS), medium vegetation or thick trees.

This experiment was run in a wooded area in the UK and in the rainforest at the Danau Girang field centre in Malaysia. The specified maximum range of 802.11g is 120m. When considering attenuation and obstacles we were expecting the signal to be reduced by up to 50% in the UK. However, we found that we received a maximum range of 30m, with LOS. Figure 9 shows the results we experienced, while testing in Cardiff, some of the drops in signal can be attributed to dense foliage and readings that were not LOS, but a maximum range of 31m, with an SNR of 29.5 dBm, is considerably less than we expected.

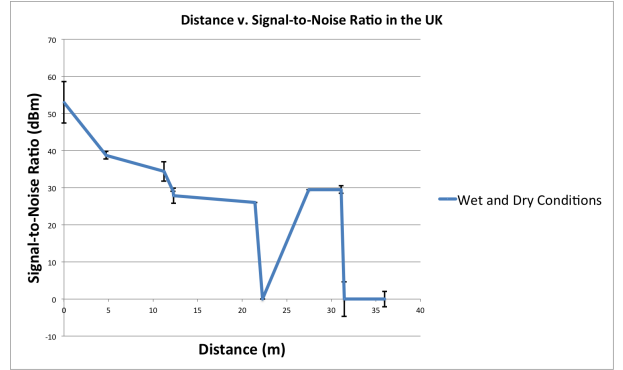


Figure 9: Signal-to-Noise Ratio for Wi-Fi in UK Woodland

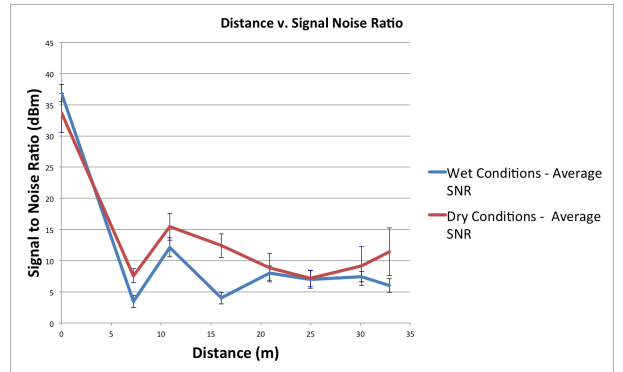


Figure 10: Signal-to-Noise Ratio for Wi-Fi in Malaysian Rainforest

The graph does show a drop at 22m, this was due to the dense foliage that restricted the LOS between the base station and the receiving node, with five runs of this test we observed the same results. The primary aim of this experiment was to prove the viability of Wi-Fi and to ensure our application functioned as intended, which it did. Further experiments could have been run to remove the anomaly but the results of the experiments in Danau Girang were the more important results.

Despite the poor range from the tests in the UK, it was consistent with other studies reporting signal degradation of up to 78% in areas with moderate foliage. We visited Danau Girang in 2011 to gather the requirements of the network and ensure the hardware is able to survive the humidity. Range experiments were run in the rainforest to see if a more humid environment impacts range any further, Figure 10 shows this.

Comparing figures 9 and 10 shows that the maximum distance to receive a signal is approximately the same in Malaysia as it is in the UK. There are more signal drops but this

seems to be due to denser foliage, blocking the line of sight. However, it does suggest that the humid environment of the rainforest does not have a significant impact on the received signal. It is clear that the denser rainforest does impact the signal-to-noise ratio in a much shorter distance from the base station but a link is still made, allowing for a successful transmission of data.

Due to the poor results of these experiments we researched alternative methods to increase the range without impacting the environment the network is to be deployed in. We considered using intermediate Data Collection nodes, not attached to cameras, to account for the lack of range but, because some cameras can be up to 1km apart, we would need more than 30 nodes to create a connection between two locations.

We also researched wireless technologies that are more common in sensor networks. This does mean that the data rate is not as high as Wi-Fi and error correction in packet streams is not always as robust, but it is more suited to sensor networks, using less power and providing longer range.

Finally, we considered using the researchers or animals at Danau Girang, as 'data mules', creating temporary links between nodes while they are in the forest. However, the trip to Danau Girang yielded the information that researchers generally do not cover those distances in the forest and data delivery would be sporadic.

Although the range of Wi-Fi is poor, for our requirements, in both Malaysia and the UK, it has shown that the results we experience in the UK are very similar to the results in Malaysia. This means that tests we run in the UK should be indicative of what we can expect in Danau Girang.

Due to the poor range results of Wi-Fi, we created a second prototype of the network, using Digimesh as the communication medium. Digimesh is a proprietary wireless protocol, based on the 802.15.4 standard and designed for devices with limited power. Using the same frequency as Wi-Fi, Digimesh has been reported to provide 7km of range, with a data rate of 250kbps.

In our prototype implementation, we are using Waspnote sensor boards [9], a general purpose Data Collection node that is capable of transmitting through various communication mediums. Our Waspnotes are provided with Digimesh modules and a 2GB SD card to store sensed data.

When testing the range of the waspnote, we followed a similar method to that which is outlined in Section 6.2, although we used Waspnote sensor boards, equipped with 802.15.4 Digimesh modules. These modules allow for native support of mesh networking that is more advanced than that of Digimesh on its own.

One board is static in a location and running a C++ application to poll for nodes in the network, once one is found it sends a message to the node every 10 seconds. The second board is set to scan the network and receive packets as soon as a base node is found, this node is then moved to different locations.

The receiving node prints out variables related to the received packet, such as: RSSI, source MAC address and packet ID. However, not all packets are received so the RSSI can display 0 if there are errors reading or if packet collision occurs. We found this to affect the results and have just used the two nodes to identify the maximum distance they can be apart, while maintaining a stable connection.

The initial results for the range tests have proven positive and it does seem to be a viable solution to account for the lack of range, when using Wi-Fi. As the frequency is the same as 802.11g, thus licensing it for worldwide use, we are expecting similar results for range in Malaysia but we will need to carry out more extensive tests, at Danau Girang, in June.

Thus far, these experiments have only been run in a moderately vegetated area in the UK which yielded 497m of range. Limitations with buildings preventing us from testing any further but the signal strength still proved to be strong. Although these are positive results, more detailed experiments in Malaysia are required to justify Digimesh as a viable communication method.

7. RELATED WORK

There has been a lot of work in the use of WSNs for habitat monitoring but there is a subset of this research that is most relevant to our work. One of the more notable is the Instant Wild project, a network of 50 cameras in various locations around the world [17], tasked with taking pictures when motion is detected and uploading them to the Instant Wild servers. The aim of Instant Wild is to crowd-source sensed data, providing a public web interface to all of the images taken by 50 cameras. Users of the website can view recent images, and thumbnails of possible animals that may be in the image. Clicking on these thumbnails counts as a vote and all of these votes are shown, taking the majority vote as the general consensus of the image contents.

The deployment of sensors on Great Duck Island [13] for habitat monitoring has proven successful and a simple architecture for clusters of sensors to collect data about the island and its inhabitants outlines how sensed data is made globally accessible. The readings from these sensors are sent to a gateway, which then forwards all information to the base station, where it is stored. A remote link to the base station allows external access and providing remote users with sensed data for processing.

There has been research in using local knowledge to aid the deployment of sensors in harsh environments, [14] uses the local knowledge of the conditions of the environment for the nodes to modify the cases and to coat the sensors themselves before they are deployed in a harsh, glacial environment.

Local knowledge of the topology of a WSN has also been used to improve the efficiency of routing in a network, a framework is introduced in [12] that uses locations of nearby nodes to make energy efficient decisions on routing packets to improve the performance of a network, while not affecting the battery life.

The Digimesh protocol is becoming increasingly popular in

WSNs, due to its flexible support for mesh networking. One such example is a WSN that requires long range and long term deployment with little human maintenance to detect forest fires [5].

Context Aware Systems (CAS) use multiple sources of information to understand a situation, this generally involves a user and his, or her, environment. In [21], the authors explore how WSNs can be the source of information for a CAS. This allows the handling of multiple sources from a heterogeneous network by the sensor middleware, passing on processed data to the CAS. The main aim of this is to allow a single CAS to be applicable to a number of domains instead of being bespoke for a set of requirements in a particular domain.

BScope is an architecture for WSNs that uses an inference engine to apply contextual information to sensed data [11], this is presented for the use in assisted living environments, using sensors to understand the movements of elderly people within their homes. Contextual information is also used in BScope to perform consistency checks that the network is performing to its required specifications and checks for node failures, poor links between nodes or any outlying errors.

Our research into applying knowledge bases to images is not the only research that has married image processing with other sources of knowledge. Higher level semantics in Content Based Image Retrieval (CBIR) are explored in [10] and the authors have classified this work into five categories. An example of these categories is the use of textual or visual sources on the internet. This approach is similar to ours but simply involves using a larger, less specific knowledge base to retrieve images with content that matches a specified query.

Cyclops is a bespoke Data Processing node that has been developed to take images and perform processing to detect objects or gesture recognition. The performance of the Cyclops node is shown in [15] and it is highlighted that these nodes can be combined with other nodes in heterogeneous WSNs.

8. CONCLUSION

This paper proposes K-HAS, an architecture for wireless sensor networks to enable in-network processing for the classification of sensed data. Initial experiments have shown that Digimesh is a suitable long range protocol for the transmission of sensing data. The processing of sensed data on Data Aggregation nodes has proven to be accurate in extracting relevant sections from images.

One of our primary aims when designing K-HAS was to create an architecture for a sensor network that does not require technical expertise to deploy or maintain. In the case of Danau Girang, this means that a computer scientist would not be required to be on-site at all times and the network could be maintained by the existing researchers at the field centre. We have created a web interface that runs with our chosen sensor middleware, allowing users to change the position of cameras and access sensed data from the database, without the need to have knowledge of SQL.

Ascertaining the distinction between the various capabilities

of sensors, we have defined three categories that can be used to aid the decision of which sensors are suitable for WSNs tasked with a particular purpose. Using these categories, we have created a three tier architecture to allow sensors to apply knowledge of their environment, in order to classify the data before it reaches the base station.

We have proposed a middle tier, with nodes that serve a subset of the network, tasked with using local knowledge to pre-process sensed data, before it reaches the base station. Our proposed upper tier allows a Data Aggregation node to act as more than just a data store, providing custom alerts for different users of the network, dependent on the data they require, and allowing global access to the sensed data.

Preliminary tests, on hardware, software and communication protocols, have proven to be positive but further testing will be required to test the full functionality of K-HAS.

K-HAS provides a knowledge base layer on top of a sensor middleware to classify aggregated sensed data at the base station. Currently, the three tiers outlined have been developed, and tested individually. We plan to finish development on the Base Tier to integrate GSN with the knowledge base to provide classifications at the upper tier.

K-HAS is intended to be generic for any WSN, regardless of domain, location or the type of data it has been tasked to sense. We use Danau Girang as an example as it is our current testbed for our prototype network.

At present, the images are being processed in sets of 3 as they arrive, independent of other sets, we plan to modify our processing implementation to store a background model of all the images from a particular camera and create a comparison between the model and the image sets that arrive. We hope that this will reduce the amount of interesting images classed as false triggers but the dynamicity of the rainforest makes the background of camera images change dramatically during a 3 month deployment.

We plan on testing K-HAS with various topologies to test its performance overall and maximise the performance of each tier. Adding wirelessly capable cameras could mean that one Data Collection node would be able to handle images taken by multiple cameras. An example of this could be two cameras, located opposite each other, deployed on a path. Our current topology requires two Data Collection nodes, one for each camera, but a only one would be required if the cameras were wireless communication-enabled. This would also assist in extracting local knowledge from images and to confirm classifications, without the need for a researcher, simply by checking if the two cameras triggered at the same time and comparing the classifications of the two image sets on the Data Processing nodes.

A visit to Danau Girang is planned for 2012 to test the wireless range of Digimesh in the rainforest and to run more tests on the individual components of K-HAS. This visit will also allow us to use the knowledge of researchers resident at Danau Girang to classify a large set of images to run more extensive tests on our image processing approach. During this visit, we expect to deploy a small scale test network,

involving one or two wildlife cameras. This will run for the duration of our visit and, if it proves to be stable, we plan to leave a long term deployment, with remote access. This allows us to test the tiers of K-HAS as well as allowing us to build a knowledge base from the classification of images, made by researchers, that can be used as training data.

Interest has also been shown by the Sabah Wildlife Department at the possible use of this network to detect hunters as well as animals, tasking the network with two purposes. This would require using the Wildlife Department as a second base station and sending all images that contain humans to that base station and all others would be routed to Danau Girang. We would expect this ‘filtering’ of sensed data would be made at the middle tier.

9. ACKNOWLEDGEMENTS

The authors would like to thank the researchers and workers at Danau Girang for their invaluable assistance and the Sabah Wildlife Department for allowing the use of the Lower Kinabatangan Wildlife Sanctuary.

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