

# AN ENTROPY-BASED COMPUTATIONAL ALGORITHM DECISION FUSION IN SENSOR-GRID COMPUTING

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## **Abstract**

*This piece of work contributes to sensor-grid computing by attenuating latency in the computation of the data deployment from the decision fusion centre of the sensor network to the Grid computing architecture. With the application of the Bayesian network computational processes which can first be applied as a computing algorithm, the sensors and the Optimal Decision Fusion (ODF) centre can be used to obtain vital information on some hazardous environment such as in military zone or from unmanned orbit mission using the Grid computing facilities in some secured state. The information so obtained must first be filtered to remove the Gaussian noise in the disseminating information of the hazardous source using Shannon's entropy algorithm which then predict coherently some well refined unbiased information. The conversion of the decision fusion into binary expedites the processing of the data from the sensor network hazardous environment and made to assembly in the grid computing remote environment from the Internet network. Many exposures can be identified to improve the Sensor-Grid computing environment where vital conflicting scenarios based on the data can be mined using machining learning algorithms. This paper is concerned with making predictive suggestion on the need to harness the sensors with the grid computing environments if worthwhile algorithms can be developed to meet the targets.*

**Keywords:** *Decision fusion, Data fusion, Maximum a Posteriori, Marginal likelihood, Prior, Entropy, Sensor-grid, Optimal Decision Fusion, Shannon's information, (SensorML) and Bayesian Network.*

## **1. Introduction**

The objective of this paper is based on the level of the Author's abstraction for which data information can be processed based-on fusion centres which can be disseminated on the grid computing environment and to the web. He adduces that information acquired from the sensors from a given hazardous space that can be mined using the web data mining algorithms. The data mining can be achieved using various computing functionality such as the Bayesian network algorithms. The acquired refined information can used to predict space functionalities. The picture of this level of abstraction is solemnly based on theoretical analysis using models as information entropy as defined by Shannon in 1949 to buttress in his level of abstraction. The Author speculates that with well established algorithm that could be deployed on the sensors which could act as unmanned devices in some hazardous environment, information can be deployed on the Grid computing environment from such sensors through the Internet from which such information can be mined. The algorithm is not specified; but left as a theoretical research assumption which could be harnessed on the Grid.

Data Fusion is defined as "a multilevel multifaceted process dealing with detection, association, correlation, estimation and combination of data and information from multiple sources to achieve refined state and identity estimation, and complete and timely assessments of situations and threats" [3]. The combination of data from multiple sensors is called multi-sensor Data. Data

fusion is the process of putting together information obtained from many heterogeneous sensor detectors, on many platforms, into a single composite picture of the environment.

Wireless sensor networks are currently the area under intensive research within the recent years. Sensors generate data that must be processed, filtered, interpreted, and archived in order to provide a useful infrastructure to the users. Sensors deployments are often untethered, and their energy resources need to be optimized to ensure long lifetime productivity [25]. In view of this, we are observing in this research paper the absorption of raw packets of information from the surrounding sensors networks which after some consideration by the sensor nodes, take decisions that are deployed into the Internet networks and then to the Grid computing environment for final processing. These sources of information absorbed by the sensor nodes are first converted into electrical signals wavelet packets [34]; which are further, deployed within the configured networks to decision fusion centers in the sensor networks topology and to the Internet network space. The decision fusion information deployed at centers need to be decomposed into wavelets using the entropy criteria to reduce inherent noises; which resultants under classifications are then made available for deployment to the grid computing environment. Thus minimizes the latency in the sensor-grid hierarchy topology in both directions of the information processing.

Sensor resources in wireless sensor networks are resource-constrained. Their processing power and communication bandwidth have limited sensing capacity. With the deployment of the sensor over a Wide Area Network (WAN), wireless sensor network has substantial data acquisition and processing capability. Hence, wireless sensor networks are important distributed computing resources that can be shared by different users and applications on the Grid computing architecture.

The grid evolved as a stands-based approach for the coordinated sharing of distributed and heterogeneous resources to solve large-scale problems in dynamic virtual organization [7]. Grid computing and sensor networks may operate in parallel in the same virtual organizations (VOs) locations. The two technological systems are enabled to leverage the services of the VOs that form the Grid heterogeneous computational servers connected by high-speed network connections. Middleware technologies such as Gridbus Project [1], Globus [2] and Legion [6] enable secure and convenient sharing of resources such as CPU, memory, storage, content and databases by users and applications. As clearly enunciated in [18], much of the existing developments in grid computing have focused on compute grids and data grids. A compute grid provides distributed computational resources to meet the computational requirements of applications, while a data grid provides seamless access to large amounts of distributed data and storage resources.

We envisioned that the harnessing of sensor technologies with the grid computing on the same platform will complement strength of computing services and characteristics of sensors networks. As observed in [1], sensor-grid computing combines real-time data about environment with vast computational resources. Accordingly, this enables the construction of real-time models and databases of the environment and physical processes as they are unfold, from which high-valued computations like decision-making, analysis, data mining, optimization and prediction can be carried out to generate “on-the fly” results. This powerful combination would enable, for instance, effective early warning for some natural disasters and real-time business process optimization. Reference [18] notes that sensor grid provides seamless access to a wide variety of resources in pervasive manner. Advanced techniques in artificial intelligence, data fusion, data mining distributed database processing can be applied to make sense of the sensor data and generate new knowledge of the environment. The results can in turn be used to optimize the operation of the sensors, or influence the operation of the actuators to change the environment. Thus sensors grids are well suited for adaptive and pervasive computing applications.

Sensors are generally equipped with data processing and capabilities. The sensing circuit measures parameters from the environment surrounding the sensor and transforms them into electrical signals [34]. Processing such signals reveal some properties about the objects located

and/or events happening in the vicinity of the sensors. Typically, the sensors send such sensed data, usually via radio transmitter, to a base or command node, either periodically or based on events. The command node may be statically located in the vicinity of the sensors or it can be mobile so that it can move around the sensors and collect data. In either case, the command node cannot be reached efficiently by all sensors in the system. To avoid long haul communication with the command node some high-energy nodes called gateways are typically deployed into the network. These gateways, group sensors to form distinct clusters in the system and manage the network system in the cluster, perform fusion to correlate sensor reports and organize sensors by activating a subset relevant to required missions or tasks. They also have the potential of monitoring the environment and habitat, healthcare monitoring of patients, weather monitoring and forecasting, military and homeland security surveillance, tracking of goods and manufacturing processes, safety monitoring of physical structures and construction sites, smart homes and offices, and many other uses that we can not at moment imagine [18].

Sensor grid is in its formative stage of research development. We abstract that the application of Naives Bayesian Network would make an added contribution to the fast accelerated developing field. The Naïve Bayesian Network algorithm will enable us construct hierarchical sensor-grid architecture as proposed by [7].

The rest of this paper is organized as follows: Section 2 gives review of the sensor-grid computing. Sensor-Grid computing is grouped into three categories. It equally dwelt on the decision fusion and data fusion methods. Section 3 is grouped into 3 subsections. The first section gives us a periscope of the sensor-grid computing environment in terms of its network connection-the centralized and the decentralized connections and their merits. The Bayesian network was briefly introduced. Subsection 3.1 is concerned with the distributed decentralized sensor network architecture. In subsection 3.2, we dealt with the formulation of the problem. While in section 3.3, the optimal decision taking using the Bayes theorem and Information entropy were the optimization weapon and encoding weapons used respectively. Section 4, discussed the research issues. Sections were proffered on how to improve the sensor-grid computing architecture. Finally, make conclusion and future research to the research work.

## 2. Related work

There are multiple existing works on the intersecting fields of sensor networks and grid computing which can be rightly grouped into three categories:

- (a) ‘sensorwebs’
- (b) sensors to grid, and
- (c) Sensor networks to grid

In the first category of ‘sensorwebs’, many different kinds of sensors are connected together through middleware to enable timely and secure access to sensor readings. Examples are the SensorNet effort by the Oak Ridge National Laboratories (ORNL) and NIST (USA) which aims to collect sensor data from different places to facilitate the operations of the emergency services; the IristNet effort by Intel to create the ‘seeing’ Internet by enabling data collection and storage, and the support of rich queries over the Internet; and the defence (USA) ForceNet which integrates many kinds sensor data to support air, sea and instruments to the grid to facilitate collaborative scientific research and visualization. Examples are the efforts by the Internet2 and the eScience communities in areas such as the collaborative design of aircraft engines and environment monitoring; DiscoveryNet (Imperial College UK) which aims to perform knowledge discovery and air pollution monitoring; earthquake science efforts by the crisisGrid team (Indiana University USA) and iSERVO (International Solid Earth Research Virtual Observatory). In the third category

of sensor networks to grid, the aim is mainly to use grid web services to integrate sensor networks and enable queries on the 'Live' data.

Decision fusion and data fusion methods that have found applications in multi-modal multimedia signal processing [13], [3], [6], decentralized detection [1], collaborative sensor network signal processing [5], and the like. With decision fusion, individual component decision makers (pattern classifiers) report their own local decisions (classification results) to a common fusion center where a final consensus decision will be made. In doing so, only the local decisions, rather than the raw data, needs to be transmitted to the fusion center. If a local decision can be represented by an integer  $\{n; 1 \leq n \leq N\}$ , then it can be encoded using  $\log_2 N$  bits. Thus, transmitting a decision to the fusion center, rather than the raw data sample, this often represents a significant saving in communication bandwidth. For applications where communication cost is high, such as a wireless sensor network, decision fusion is advantageous.

With the recent development in web services, the Grid computing is fast growing into a utility computing paradigm. This is due to the accelerated utility of the service-oriented architecture (SOA) as a cornerstone. As observed above, SOA is not fully developed and need more research developments to incorporate more services in the sensorgrid computing environment. SOA enables the discovery, access and sharing of services, data, computational and communication resources in grid by many users.

Sensor-Grid Computing components are implemented on the Grid architecture using the Globus Toolkit 3 (GT3) Globus (2006) which conforms to the open Grid Services Infrastructure (OGSI) standard. The Globus Toolkit version 4 software provides a variety of components and capabilities, including the following [19]:

- A set of service implementations focused on infrastructure and management
- Tools for building new Web services, in Java, C, and Python
- A powerful standards-based security infrastructure.
- Both client APIs (in different languages) and command line programs for accessing these various services and capabilities.
- Detailed documentation on these various components, their interfaces, and how they can be used to build applications.

These components incorporate other subsystems to enrich ecosystem and tools that build on, or interoperate with, GT components-and a wide variety of applications in many domains.

The Sensor-Grid network generates volatile amount of information that needs to be properly controlled or fall into the hands of some maniacs. The GSI security protocol provides secure communications and a "single sign on" feature for users who use the multiple resources on the grid services architecture. The Global Grid Forum developed the specification for the open Grid Services Architecture (OGSA) [21] based on the concept of Grid services. The grid services architecture enables resources to be dynamically discovered and shared. The Open Grid Services Infrastructure (OGSI) is the first specification to implement the OGSA framework, and Globus Toolkit 3 is the implementation of the OGSI specifications. Since the Sensor-Grid architecture leverages these existing and evolving grid middle standards and tools, it is necessary it takes the same physical hierarchical architecture as the Grid architecture. This will aid our computations using the Bayesian networks Maximum a posterior (MAP) algorithm [15]. The network at this condition is classified into tiers at which level we consider the parameters explicitly.

### 3. The Analytical Theory of the Decision fusion

Sensor nodes in sensor-grid networks are connected via wireless ad hoc networks. The sensor nodes in this wireless configuration have low-bandwidth, high latency, and unreliable. The connection of the nodes are dynamic and may be intermittent and susceptible to faults due to noise and signal degradation caused by environmental factors. The networks are based on standard internet protocols such as TCP/IP, HTTP, and FTP etc. On the other hand, wireless sensor networks are often based on proprietary protocols, especially for the MAC protocol and routing protocol [27].

One sure way to achieve sensor-grid computing is simply to connect and interface sensors and sensor networks to the grid and let all computation take place there. The Grid will then issue commands to the appropriate actuators. In this case, all that is needed are high-speed communication links between the sensor-actuator nodes and the grid. This is referred to as the centralized Sensor-Grid architecture [5, 28]. However, despite the seemingly rapid connectivity of the centralized approach, it has many serious drawbacks. Some of these are; it leads to excessive communications in the sensor network which rapidly depletes the batteries since long range wireless communications is expensive compared to local computation. In addition to this, it does not take advantage of the in-work processing capability of sensor networks which permits computations to be carried out close to the source or the sensed data. In the event of communication failure, such as when wireless communication in the sensor network is unavailable, sometimes due to interferences, the entire system collapses. Other drawbacks that is always glaringly manifested may include long latencies before results are available on the field since they have to be communicated back from the grid, and possible overloading of the Grid; but this is hardly sensed [5].

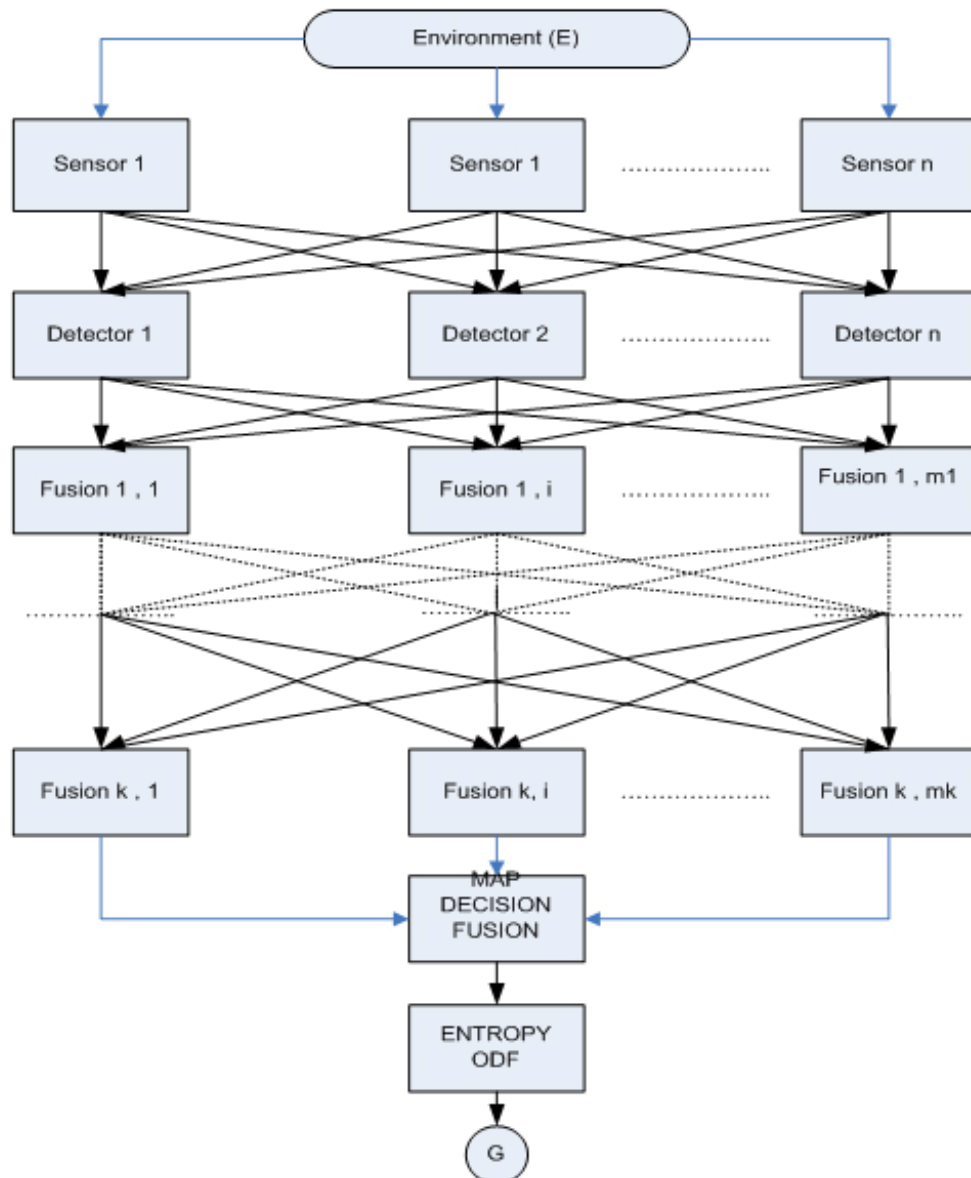
Another method of connecting the sensor networks to the grid architecture; and which is more robust and efficient, is the decentralized sensor-grid computing (see figure 1 below). This approach executes on a distributed Sensor-Grid architecture and alleviates most of the drawbacks experienced by the centralized scheme. The distributed sensor-grid computing scheme involves in-network processing within the sensor network and at various levels several possible configurations of the sensor-grid architecture. This paper gives focus to the distributed decentralized sensor-grid computing only due to the inherent benefits it has against the centralized approach. The weapon of modeling is the Bayesian Network algorithm.

A Bayesian network is a directed acyclic graph (DAG) with nodes that represent events in a domain. In our case, the nodes are the sensors nodes with events consisting of raw information from the network topological surroundings. These events are connected with direct links, which represent an association or causal relationship between them. When a link represents an association, the direction is defined according to order of time in which the events happen, that is, the link starts from the preceding event. When a link represents a causal relationship, the link starts from the causal event as presented in figure 1 below.

#### 3.1. The Distributed Decentralized Sensor Computing Approach

This approach of looking at the Sensor architectural distributed connection is highly plausible due to its computational application in analytics, data mining, optimization and prediction. Such areas as distributed information fusion, classification application and event detection; and distributed autonomous decision-making application are looked into in this section as two examples of sensor-grid computing on the sensor-grid architecture. The distributed information, event detection and classification are categorized into two stages; namely:

- (i) Decision fusion
- (ii) Data or value fusion



**Figure 1: Multiple sensors and detectors layers decision fusion network**

### Decision Fusion

The Decision Fusion is statistically tractable and independent. In this case, classification is done at individual sensor nodes or sensing modalities and the classification results are combined or fused at the centre as (depicted in figure 1) in different manners, such as by applying the product rule on the likelihood estimates. Figure 1 shows hierarchical sensor-grid architecture. The information is

Collected from the environment or space through wireless processes and receives by the upper sensors; these are sent to the detectors in form of electrical signals; other configurations follow suite. Decision Fusion requires a classification operation to be applied on either an  $n$  or  $Mn$ -dimensional feature vector at each sensor node, followed by the communication of  $(K-1)$  decisions to fusion centre and the application of a Decision Fusion algorithm on the  $K$  component decisions. The decisions fusion centre connects to the filtered entropy node in wireless pattern which may connect to the Grid computing either by wireless or direct connectivity for further processing.

### Data or Value Fusion

This feature is done when different measurements yield correlated information. In the Data or Value Fusion features, vectors from individual sensors are concatenated and classification algorithm yield better classification performance, it is more expensive to implement from the communication and computational point of outlooks. We have in reference [28] this logical presentation as a mathematical deduction alluring acceptance. At  $M$  sensing modalities at each sensor node,  $K$  sensor nodes and  $n$  dimensions in each measurement, data fusion typically requires the transmission of  $(K-1)Mn$  values to the Fusion centre (which is one of the  $K$  sensor nodes) and the classification algorithm these would need to operate on a  $KMn$  – dimensional concatenated feature vector.

### 3.2. Formulation of the Problem

Based on the algorithm proposed by [27], we consider a decision fusion architecture (as depicted by figure1) which consists of a fusion centre and  $K$  distributed sensors. These sensors observe a common characteristic vector  $x$ . Each of these sensors is capable of making rational decision which takes a decision  $d(x)$  that maps  $x$  into a set of class  $N$  label  $C = \{C_1, C_2, \dots, C_n\}$ . The feature vector  $x$  at the fusion centre maybe viewed as a concatenated vector. Each sensor in the network uses a portion of this feature vector  $x$  giving raise to variation of the decision rules implemented on individual sensors. We abstractedly believed that each of these sensors will forward its local decision  $d_k \in C_n$  to the fusion centre. Therefore each fusion centre will receive a  $K \times 1$  decision vector  $d = [d_1, d_k, \dots, d_n]$  and this may be conceptually deduced using confusion matrix.

### Decision rule

In statistical pattern classification [28], a sample  $x$  is assumed to be drawn from a probability distribution with a probability distribution density  $p.d.f$   $p(x)$ . In Bayesian network, the relationship between events is defined as the conditional probability, which is the probability of event  $X$  and  $C$  respectively. The conditional probability is calculated using Bayes theorem [26]. The probability that the feature vector  $x$  is in  $C_n$  is defined as  $P(x \in C_n) = P(C_n)$  and is known as the prior probability. The likelihood that a sample will assume a specific feature vector  $x \in C_n$  is denoted by the conditional probability  $P(x \in C_n) = P(C_n \setminus x \in C_n)$ . Now with the Bayesian network classifiers [9, 10, 11, 13, 14, and 15], the probability for a particular sample to belong to a given class  $C_n$  and a given value of  $x$  sample is denoted by the a posteriori probability class and expressed as:

$$P(x \in C_n \setminus x) = P(C_n \setminus x) = \frac{P(x \setminus C_n)P(C_n)}{P(x)} \quad (1)$$

where  $P(x \setminus C_n)$  is the conditional probability of the event  $x$  given the event  $C_n$ . Thus as can be seen, Bayesian networks can considered as a network of events connected by the probabilistic dependencies between them. Events that have no causal relationship are called marginal conditional probability distributions over the network. In equation (1),  $P(x \setminus C_n)$  is called the likelihood of the data, given the Prior probability distribution. Equation (1) provides the principle of Bayesian updating, where the prior probability distribution is updated using the likelihood of the observed data. This shows that the Bayesian can be recalculated anytime new information becomes available.

We apply a naïve-Bayes classifier to consider the decision rule. By definition, a Naïve-Bayes classifier is a network, in which a single node represents predictor variables. Figure 1 is a clear conception of the naïve Bayes classifier distributive network. Decision rule is a mapping from the

feature vector  $x$  to an element in the class label set  $C$ ; that is,  $d(x) \in C$ . If  $x \in C_n$  and  $x = C_n$ , then a correct classification (decision) is made; otherwise, a misclassification is made. The maximum a posteriori (MAP) classifier chooses the class label amongst the  $N$  class labels that yields the largest maximum a posteriori discrete variables:

$$d(x) = \arg \max_x P(C_n/x) \tag{2}$$

where  $d(x) = n$  means  $d(x) = C_n$

The statistical maximum a posteriori (MAP) classifier stipulates that for a continuous likelihood parameter, in order to maximize the probability of a correct classification (and hence minimize the probability of miscalculation); the decision rule must choose the class label among all  $N$  classes that yields maximum a posteriori probability. That is to say,

$$P_c = \int \sum_{n=1}^N P(d(x) = C_n \mid x \in C_n) P(C_n) p(x) dx \tag{3}$$

Equation (3) has no bearing with our work currently; but it clearly shows that it can be applied to the decision fusion problem when the sensors are considered to be deployed in thousands within a compacted smaller geographical region; the region therefore may be considered as a continuum.

### 3.3. Optimal decision fusion (ODF)

In a characteristic dexterity as [18, 28], we consider a sensor or Sensor network configuration that consists of fusion centre and  $K$  distributed sensor nodes. Each sensor node observes feature vector  $x$  and applies a classification algorithm, such as the MAP classifier described already, to arrive at a local decision  $d(x) \in C$ . The  $K$  sensors nodes forward their local decisions  $d_k \in C$  to the fusion centre which forms a  $K \times 1$  decision vector  $d(x) = [d_1, d_2, \dots, d_k]$ .

A decision fusion as devised by [28] are referred to as the ODF. This consists of a set of  $N^k$  disjoint regions, denoted as  $\{r_m; 1 \leq m \leq N^k\}$ . Every unique decision vector  $x \in r_m$  maps to  $d(m)$ . Following the MAP principle at the fusion centre, we have

$$l(d/m) = C_n \text{ if } P(C_{n^*} \mid d(m)) > P(C_n \mid d(m)) \tag{4}$$

For  $n \neq n^*$ . Using Bayes' rule, if  $P(x \in r_m) \neq 0$ , then

$$\begin{aligned} P(C_n/d(m)) &= \frac{P(d = d(m) \mid x \in C_n) P(x \in C_n)}{P(x \in r_m)} \\ &= \frac{P(d = d(m); x \in C_n)}{P(x \in r_m)} \\ &= \frac{|\{x \mid x \in r_m \cap C_n\}|}{|\{x \mid x \in r_m\}|} \end{aligned} \tag{5}$$

where  $|\{\dots\}|$  is the cardinality number of the set. Hence, The MAP classification label  $C_n$  for  $r_m$  can be determined by

$$n^* = \arg \max_x |\{x \mid x \in r_m \cap C_n\}| \tag{6}$$

when the feature space is discrete. Essentially, this means that the class labels of  $d(m)$  should be assigned according to a majority vote of class labels among all  $x \in r_m$ .

We assume at this point that the optimal ODF of disjoint regions deployed to the centre by equation (6) consists of Gaussian noises of wavelet packets. Thus, there is a need for further minimizing the largest maximum wavelet packets of the disjoint regions of equation (6) by decomposing and compressing it. This is achievable by the application of Claude Shannon information theory otherwise, known as entropy information theory. In doing this analysis, we will need the conditional probabilities of the outcome at the decision centre which in this case, is the set



of the ODF deployed to the fusion centre from individual sensors in the network in figure 1. The deployment of ODF de-noised aggregated data classifiers of the entropy information application output reduces latency in the sensor-grid computing environment to the minimum in both directions, that is, from the client to the Globus toolkit and from it to the client.

Therefore, let  $X$  be a discrete feature vector on a finite set  $X = \{d_1, d_2, \dots, d_n\}$  at the fusion centre, with probability distribution function  $p(d) = \Pr(X = d)$ . The entropy  $H(X)$  of  $X$  can be minimized such that the true parameter  $\hat{\theta}_{mee}$  of the marginal likelihood  $P(d = \theta_{mee} | x \in C_n)$  can be estimated, this estimation removes the Gaussian-noise (disturbance(s)) that may be incorporated in equation [6]. With the removal of this inherent disturbance, the minimum estimate of the marginal likelihood is obtained. Being the optimal minimum, latency will be minimized in the sensor-grid computing processing hierarchies. Now by applying the model in [2] the estimator based on the law of large number [35] is expressible as:

$$H(d) = -\frac{1}{N} \sum_{d \in D} \log_b p(d) \quad (7)$$

The “plug-in” estimator [36] can then be expressed:

$$\hat{H}(d) = \int_{-f}^f \hat{p}_g(d) \log \hat{p}_g(d) dx \quad (8)$$

Therefore the minimum entropy estimator for the parameter  $\hat{\theta}_{mee}$  is defined to be:

$$\theta_{MEE} = \arg \min(\hat{H}(d)) = \arg \min(\hat{H}(y - \theta^T u)) \quad (9)$$

The logarithm [7] is usually taken to be in base 2, in which case, the entropy is measured in “bits” or to base e, hence under such condition,  $H(d)$  is measured in “nats”. The entropy of  $X$  does not depend on the actual values of  $X$ ; it only depends on p.d.f.  $p(d)$ . The definition of Shannon’s entropy [34] can be written as an expectation:

$$H(X) = -E[\log_b p(d)] \quad (10)$$

The quantity  $\log_b p(d)$  in equation (10) is interpreted as the estimated information content of the discrete estimate of the content  $d \in X$ ; is called the Hartley information of  $d$ . Hence, the Shannon’s entropy is the average measurement of information contained in ODF  $X$ ; it is also the disturbance removed after the actual outcome of  $X$  is revealed.

Equation (9) completely gives the desired de-noised ODF that is decomposed and compressed by the entropy theory; and thus, is worthy of being deployed to the Grid computing for final analysis and interpretation of the sensor information absorbed from the sensor network environment at the Grid computing environment.

At this point, we end the analytical entropy theory and deploy the output to the Grid computing environment as depicted by (G) in figure 1.

#### 4. Research Issues

Sensor-Grid is a relatively new research area such as in the deployments of standardized protocols. Presently, there are little deployments for sensor-grid aggregates for consumption purposes. In view of this non utility of the data, so many open issues are left unattended or where they have been attended to, the researchers do not have sufficient deployment experience to tell whether certain approaches will withstand the test of time. Therefore a number of issues are proliferating and interwoven that makes reposition and exposure quite intricate for lack of adequate storage and transporting media to the grid architecture. In addition to the lack of the fundamental wherewithal in a sensor-grid computing environment, there is a need for security in order to safely

manage routing configuration. Sensor signal packets or information fusion are liable to get intercepted by some unwanted person. This is can cause serious devastation if fallen into the hands of unfriendly environment during military interventions.

Sensors source of energy is none replenishing; this area therefore needs extensive research such as to improve the life longevity of these nodes especially during espionage in unfriendly localities. Failure of the non-replenishing energy may lead to serious excommunication; its attending consequence is better left to human imagination. Hence, sensor devices need to be constructed in a manner that they only diffuse information to the targeted fusion centers.

Sensors interact with one another within close proximity to form networks; this may give raise to poor connectivity and result to intricate interferences that may cause latency and confusion with issuance of undesirable noises at the fusion centers.

Other issues that need to be addressed amongst others include energy management (as aforementioned), coverage, localization, medium access control, routing and transport, security, as well as distributed information processing algorithms for target tracking, information fusion, inference, optimization and data scheduling [27]. Sensor-Grid computing still has much challenging issues. Of these is the issue of efficient resource allocation to give high quality of service (QoS) and high resource utilization. Other issues are workflow management, the development of the grid and web services to facilitate discovery and access of services on the grid and security. Efficient resource allocation incorporates a number of aspects including aggregation at the grid and cluster or the sensor node-levels, Service Level Agreements (SLA) and market based mechanisms such as pricing.

In furtherance of the issues at research for the Sensor-Grid computing, this computing development has an added challenging research impacts and in such areas as in the security mission critical situations. These challenges are mostly tackled through the instrumentality of the web services and service discovery which work across both configuring systems. These web services would enhance connectivity between sensors nodes networking thus improve coordinated QoS mechanisms; also robust and scalable distributed and hierarchical algorithms so developed from the web services will give efficient queries and self-organization and adaptation in their Sensor-Grid topological architecture.

#### **4.1. Sensor-Grid Web Services and distribution**

Web services are persistent [27]. Hence the life time of the web services is likened to a container with constant contents. The utility of the services in the container by a client do not empty the contents of the web. Another advantage of the web services is that the services are accessible by multiple clients at various geographical locations in the VOs at the same time; this is the most prominent aspect of the web services scalability. Unlike the web services, Sensor-Grid computing services are transient, and thus, have limited lifetime utility services. SensorGrid Services (SGS) instances are created and destroyed at demand. The life cycle of an instance may, however, vary depending on the nature of the application. Due to this transient tendency, there is a need to device storage facilities in form of caches so that they can easily be accessible at demand.

As the grid expands its tentacles to all domains of existence, there is a need for such researches to develop such consortium as the OpenGeoSpatial Consortium's Sensor Model Language (SensorML) that is modeled to adopt SOA and web services [26] which have the following numerated aims and objectives:

1. To provide general sensor information in support of data discovery,
2. To support the geo-location and analysis of the sensor measurements,
3. To provide performance characteristics (e.g. accuracy, threshold, etc),
4. To archive fundamental properties and assumptions regarding sensor.

SensorML can describe sensor parameters independent of platform and target, as well as mathematical models which can directly map between sensor and target space. SensorML can be applied to virtually any sensor, whether in-situ or remote sensors, and whether it is mounted on a stationary or dynamic platform.

#### **4.2. Sensor and Grid Computing Network**

Landmark differences exist between the edges connection of the sensor nodes and the grid computing environment. The Sensor network emphasizes on low power wireless communications; this vis-à-vis, has limited bandwidth and time-varying channel characteristics. On the other hand, grid computing has high-speed optical network connections. Hence the web services protocols for the sensor-grids need to be designed in order to take into consideration these differences.

#### **4.3. Quality of Service in SensorGrid Architecture**

A number of QoS control mechanisms such as scheduling, admission control, buffer management and traffic regulation or shaping have been developed to archive application-level and network-level QoS [25]. These usually relate to a particular attribute such as delay or loss, or operate at a particular router or server in the system. These QoS mechanisms need to be coordinated instead of operating independently.

There are several methods to achieve coordinated QoS; for example, coordinated QoS can be viewed as a multi-agent Decision Process problem which can be solved using online stochastic optimal control techniques such as reinforcement learning (RL) [37]

This area in sensor-grid computing even the efficient querying of databases for sensor network programs demands research exposition. It is expected that databases will be distributed and replicated at a number of places in the sensor-grid architecture to facilitate efficient storage and retrieval. Hence, the usual challenges of ensuring data consistency in distributed caches and databases ought to be researched such that the added complexity of having to deal with large amount of possibly redundant real-time data from sensor networks is removed.

#### **4.4. Robust and Scalable Algorithm**

In addition to the distributed information fusion and decision-making so far studied in section 3, distributed hierarchical target-tracking for distributed control and optimization need to be critically researched and efforts on distributed algorithms which are relevant to Sensor-Grid computing be given rigorous emphasis through research.

### **5. Conclusion and future work**

In this paper, we have rigorously looked and examined the Sensor-Grid structure. Emphasis was wisely considered on the decision fusion algorithm. The mathematical theory that gave the acquisition of the ODF at the fusion center was given prominence consideration. Furthermore, using the Shannon information theory, the ODF was filtered and the end result converted to bits. This conversion speeds the deployment of the ODF to the grid computing architecture; in this case the Globus tool kit for final information processing. We have equally looked inwardly and deeply too into the necessary exposures that could enhance the development of the sensor-grid computing architecture in terms of many criteria such as the QoS, extensive harnessing of the SOA and Web Services and need for security of the general computing system. We have also overview the potential and challenges in sensor-grid computing and described how it can be implemented on different configurations of the sensorgrid architecture.

In the final analysis, the success of the sensor-grid computing environment will depend on the ability of the sensor network and grid computing research communities to work together to ensure

compatibility in the future, as well as the ability of the sensor-grid computing technology to provide real value to users and applications in the various industries.

In our next paper, however, we intend to do a thorough computational research on the application of entropy theory on sensor networks. This, we hope, would contribute in interpreting the sensors networks pieces of information locally and without having to connect to the grid computing.

## 6. References

- [1] The Gridbus Project. <http://www.gridbus.org>
- [2] Minh, T., and Debrunner V., “Minimum Entropy Estimation as a near maximum-Likelihood in system identification with non\_Gaussian noise”
- [3] Hall, D. L., and Linas J. S. (2010), “Handbook of Multisensor data fusion. Boca Raton”, FL: CRC press
- [4] Esra, C. (2005), “Performance evaluation of the mathematical programming based clustering algorithm for wireless Ad Hoc network operating in threat environment”, Thesis of master of science; Department of industrial Engineering, University of Buffalo; February,
- [5] Chen-Kong T., and Buyya R. (2005), “Sensor Grid: Integrating sensor Networks and Grid Computing”.
- [6] R. Buyya., “Economic- based Distributed Resource Management and scheduling for Grid Computing”. A PhD Thesis, Computer Science Department, University of Melbourne. April, 2002
- [7] Foster, I., C. Kesselman, and Tuecke S. (2001), “The anatomy of the Grid enabling Scalable Virtual Organizations”. Applications, 15(3);200-222
- [8] Laskey, K. B., “Computational Models for Probabilistic inference; Unit2: Graph Theory, Conditional Independence, and Bayesian Networks”.
- [9] D. Grossman, and Domingos, P., “Learning Bayesian Network classifiers by Maximizing conditional Likelihood”
- [10] Mager, D., and Tali, G (2006) “Introduction to Computational Biology lecture #18: Bayesian Networks and Directed Graphical Models”, 10:05:
- [11] Freidman N., and Machman, M. L., (1997) “Using Bayesian Networks to analyze expression Data”,
- [12] R. Gottardo, and A. E. Raftery., “Markov Chain Monte Carlo with mixtures of Singular distribution”, Technical Report no. 470, Department of statistics, University of Washington, oct.7, 2004
- [13] Jordan, M.I., and Yair W., “Probabilistic inference in graphical Models”
- [14] Freidman, N., Geiger D., and Goldesmid, M. T. (1997) “Bayesian network classifiers” Machine learning 29, 131-163;
- [15] Heckerman, D. A., (1996) “Tutorial on learning with Bayesian Networks. Microsoft Research advanced Technology Division Microsoft corporation one way Microsoft Way Redmond”, WA 980052
- [16] Akyldiz, I. F., (2002), W. S., Sankarasubramanian, and E., Cayrici, “Wireless sensor networks: a survey, computer Networks”, 38(4): 393-422
- [17] Culler, D. E., and Srivastava, M., (2004), “Overview of sensor networks. IEEE computer”, Page 41-49, August
- [18] Hock B., Protik, Weng, Y., Simon, M. T., , M, et al: Fnsor Grid: Integration of wireless sensor networks and the Grid”
- [19] Forster, I (2005)., “Globus toolkit Version 4: Software for Service-Oriented Systems”, Math & Computer Division, Argonne National Lab, IL 60439. Department of Computer Science, University of Chicago, IL 60637, USA, IFIP International Federation for Information Processing
- [20] Foster, I. and Kesselman, C. (1997): Globus “A metacomputing infrastructure toolkit”, International Journal of SuperComputer Applications, 11(2):115-128.

- [21] Foster, I. and Kesselman C., J. N., , et al (2002) “The Physiology of the grid: An open Grid Service Infrastructure WG”, Global Grid Forum, June 2002
- [22] Tuecke, S., (June 2003) “Open Grid services Infrastructure (OGSI) version 1.0”, Global Grid Forum Draft Recommendation,
- [23] Niedermayer, D. (1998), “An introduction to Bayesian Networks and their Contemporary Applications”
- [24] Freidman and Goldszmidt; [http:// www.erg.sri.com/people/moises/tutorial](http://www.erg.sri.com/people/moises/tutorial)
- [25] Tham C.<sup>1</sup> and, Buyya,<sup>2</sup>C., “Integrating Sensor Networks and Grid computing”, <sup>1</sup>Dept Electrical & Computer Engineering, National University of Singapore. Email: [electck@nus.edu.sg](mailto:electck@nus.edu.sg). <sup>2</sup>Department of Computer Science, University of Melbourne, July 2005.
- [26] [http:// www.vast.nsstc.uah.edu/SensorML/](http://www.vast.nsstc.uah.edu/SensorML/)
- [27] Tham . C., (2006) “Sensor-Grid Computing and SensorGrid architecture for Event Detection, classification and Decision-Making”, Dept Electrical & Computer Engineering, National University of Singapore. Email: [electck@nus.edu.sg](mailto:electck@nus.edu.sg)
- [28] Duate M. F., “Optimal decision Fusion for sensor network Applications in processing of first ACM conference on embedded Network sensor system 2003”, (Sensys 2003)
- [29] Dempster, P, (1968.) “A generalization of Bayesian inference. Journal of the Royal Statistical Society”
- [30] Sudano, J J, “Equivalence between belief theories and naïve bayesian fusion for systems with independent evidential data: Part 1, the theory. In proceeding of the sixth International Conference on Information Fusion”, pages 1239-1243, 2003
- [31] Sudano, J J, “Equivalence between belief theories and naïve bayesian fusion for systems with independent evidential data: Part 11, the theory. In proceeding of the sixth International Conference on Information Fusion”, pages 1239-1243, 2003
- [32] Gupta, G., and Younis, M.: Performance Evaluation of Load-Balanced Clustering of Wireless Sensor Networks
- [33] <http://www.planetmaths.org/encyclopedia /distribution2>
- [34] Ahmad, I. A., and Lin, P. E ( 1976)., “A Nonparametric Estimation of the Entropy for Absolutely Continuous Distributions.” IEEE Trans. On Information Theory
- [35] Beirland, J., Dudewicz, I., G. and Van der Meulen, E. C. Nonparametric ( )1997: Entropy Estimation: An Overview. International J. Mathematical and Statistical Sciences, vol. 6, pp. 17-39
- [36] Sulton, R., and Barto (1998): A. Reinforcement Learning: An introduction. M. T. press or neuro-dynamic programming (NDP)
- [37] Yeow, WL, Tham, CK, and Wong, LWC.(2005) A Novel Target Movement Model and Efficient Tracking in Sensors Networks”, Proceedings of the IEEE VTC 2005-Spring, Sweden 29 May-1 June.

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