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Expressing Sensor Maturity in Terms of Information Fusion: Re-defining Non-Traditional Sensing

Jayson Priest[1], Timothy Priest[2], and Angela Consoli[2]

[1]Joint and Operations Analysis Division
[2]Weapons and Combat Systems Division
Defence Science and Technology Group

DST-Group-TR-3400

ABSTRACT

In recent years, the term 'non-traditional sensing', or NTS, has seen increased usage; particularly within military parlance. This paper explores the definition of NTS, some of the technologies that are typically associated with NTS and, ultimately, questions the need for NTS as a concept. Instead, it suggests that NTS is really an artefact of perception resulting from the natural and ongoing development of sensor systems towards higher levels of data and information fusion. A light-weight model that provides a generalised mapping between increasing sensor complexity and fusion is presented as an alternative to more formal models that have been proposed previously.

RELEASE LIMITATION

Approved for public release.

UNCLASSIFIED

Produced by

Joint and Operations Analysis Division
Defence Science and Technology Group
Third Avenue
Edinburgh SA 5111

Telephone: 1300 333 362

September 2017
AR-016-953

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Executive Summary

In recent years, the term 'non-traditional sensing', or NTS, has seen increased usage; particularly within military parlance. This paper explores the definitions of both traditional and non-traditional sensors, including providing a précis of historical sensor development. Having providing a baseline definition of traditional sensing, and the driving technologies behind some of the systems that are typically associated with non-traditional sensing, the paper considers several sensing technologies that are presently associated with non-traditional sensing: hyper-spectral imaging; synthetic aperture radar and synthetic aperture sonar. Exploring what makes these technologies non-traditional, the paper ultimately questions the need for the concept of non-traditional sensing. Instead, it is suggested that NTS is simply an artefact of perception resulting from the natural and ongoing development of sensor systems towards higher levels of data and information fusion.

Given this premise, a light-weight model that provides a generalised mapping between increasing sensor complexity and fusion is presented as an alternative to more formal models that have been proposed previously. Some examples of techniques and technologies that not only provide evidence for the validity of the proposed model, but that sit higher on the non-traditional sensing 'spectrum' than those techniques presently categorised as non-traditional, are presented.

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Authors

Dr Jayson Priest
Joint and Operations Analysis Division

Jayson was awarded his Bachelor of Science (Honours I) in 1996 and his PhD in 2001 for his thesis on 'Nitriding mechanisms and the nature of the treated layer in rf plasma nitriding of austenitic stainless steel'. Since joining the Defence Science and Technology (DST) Group in early 2000, Jayson has worked on and led a number of research and development projects, including: the development of the Centre of Gravity Network Effects Tool (COGNET), the collaborative Joint Warfighting Suite for rapid prototyping, development and testing of leading-edge technologies for Joint Operations Planning. Jayson was posted in 2007 to the Australian Defence Force Warfare Centre as lead Research Scientist for Development of future Operational Planning environments and tool suites. Jayson returned to DST in 2009 as his groups systems integrator for the C3I demonstrator. In 2013 Jayson changed his research focus towards Big-Data analytics and emerging 3D visualisation systems. Jayson is presently Science Team Lead for Technology Futures Forecasting (TFF). His current research interests are in technology futures and methodologies.

Dr Timothy Priest
Weapons and Combat Systems Division

Tim was awarded his Bachelor of Science (Hons I) in 1993 and his PhD in 1998 for his thesis on 'Fiber Optic Sensing of Electromagnetic fields'. Since joining the Defence Science and Technology (DST) Group in late 1998, Tim has worked on and led a number of research and development projects, including: the development and demonstration of advanced electro-optical networking links in military systems. In 2009, Tim was posted to Washington, DC as part of the F-35 acquisition program where he became interested in Mission Data and EW reprogramming. Tim returned to Australia as the Director S&T for AIR 6000 in 2011, before returning to Adelaide in 2015. Tim is presently the acting group leader for DST's Tactical Information Integration and Interoperability (TI3) group. His present research interests include information resilience, assured interoperability and dynamic mission data reprogramming.

Dr Angela Consoli
Weapons and Combat Systems Division

Dr Angela Consoli has been with the Defence Science Technology (DST) Group since 2011. Prior to joining DST, Angela worked as a software engineer with BAE Systems Australia, working with military air mission systems. Angela graduated with a Bachelor of Engineering in Computer Systems (Honours) and Bachelor of Commerce from the University of South Australia in 2004. In 2010, Angela received her PhD in Computer Systems Engineering, which focussed on enhancing team automation using coordination and cooperation. Angela has worked on airborne mission systems, focussing on tactical information assessment and decision aiding for distributed air assets, and has written many peer-reviewed journal papers, book chapters and conference papers in these areas.

Contents

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Glossary

ADF	Australian Defence Force
AESA	Active Electronically Scanned Array
AN/APG	Designator for Airborne Fire Control Radars
ANSI	American National Standards Institute
ARGO	Autoregression with Google search data
AVIRIS	Airborne Visible / Infrared Imaging Spectrometer
C3	Communications, Command, and Control
DFIG	Data Fusion Information Group
EODAS	Electro Optical Distributed Aperture System
GPS	Global Positioning System
HSI	Hyper Spectral Imaging
ID	Identification
IEEE	Institute of Electrical and Electronics Engineers
IP	Internet Protocol
JDL	Joint Directors of Laboratories
MEMS	Micro-Electro-Mechanical Systems
NIST	National Institute of Standards and Technology
NTS	Non Traditional Sens(or)ing
SAS	Synthetic Aperture Sonar
SAR	Synthetic Aperture Radar
TS	Traditional Sens(or)ing
WIFI	IEEE 802.11b wireless networking; term coined from Wireless Fidelity.
Transducer	An object that detects events or changes in an environment and provides a corresponding physical output (e.g. thermocouple).
Sensor-system (Sensor)	An object that contains one or more transducers, any associated signal processing and an output interface to detect and qualify/quantify those changes.

Single-transducer	A sensor-system that utilises a single transducer as input to the back-end processing of the system (e.g. thermocouple-based temperature sensor).
Multi-transducer	A sensor-system that utilises multiple transducers as input to the back-end processing of the system. The multiple transducers can be in the form of a localised array (e.g. AESA radar aperture) or in a wider distributed system (e.g. F-35 EODAS).
Parameter	The physical phenomenon being measured (e.g. temperature, pressure, distance).
Single-parameter	A sensor-system that provides sensing outputs of only only one parameter (e.g. pressure, distance).
Multi-parameter	A sensor-system that combines multiple input parameters and utilises those to provide multiple output parameters (e.g. 'smart dust', 'Deep learning' image analysis and SAR).
Single-function	A sensor-system that provides sensing output related only to a single parameter (e.g. Pressure, displacement).
Multi-function	A sensor-system that provides sensing output for multiple parameters based on the inference of higher-level constructs from a single parameter (e.g. radar 'heading' and 'altitude').
Mixed-structure	A sensor system that utilises both structured and unstructured data/information sources as 'transducer' inputs (e.g. crowd-sourced GPS augmentation).

1. Introduction

1.1 What is Non-Traditional Sensing?

In recent years the term 'non-traditional sensing' (NTS) has gained popularity within military parlance. This paper explores the definition of NTS and discusses some of the technologies that are typically associated with NTS. In this context, the paper then discusses whether NTS is a defined concept, or rather relates to the ongoing development of sensor systems towards higher levels of data and information fusion; ultimately trending towards more cognitive-like sensor systems in which multiple and disparate information sources provide an integrated semantic view of the sensed environment.

1.2 What is a Sensor?

The terms 'sensor' and 'transducer' are – perhaps wrongly – often used interchangeably. The definition of a transducer, from the American National Standards Institute (ANSI), is 'a device which provides a usable output in response to a specific measurand', where the output is typically an electrical signal and the measurand is a physical quantity, property, or condition [2]. That is, a transducer is a physical item that transforms one physically measurable parameter[1] (measurand) to another physically measurable parameter.

A sensor, on the other hand, is defined by the American National Institute of Standards and Technology (NIST) as 'a transducer that converts a physical, biological or chemical parameter into an electrical signal...' [3].

However, such definitions are somewhat unfulfilling and ambiguous. For instance, do sensors have to have an electrical signal as their output? Surely mechanical ideal-gas-law pressure and temperature sensors are still sensors?

The above definitions are understandable, given the overwhelming number of transducers and sensors that are electrical in nature. It is perhaps partly because of this that the terms transducer and sensor have come to be used so interchangeably over time. However, for the purposes of this paper, it is important that we clearly delineate transducers and sensors.

To avoid ambiguity, the following, less presupposing, definitions for transducer and sensor will be used throughout this paper:

- *Transducer*: 'a device that receives a signal in the form of one type of energy and converts it to a signal in another form.' [4]

- *Sensor*: 'a device which detects or measures a physical property and records, indicates, or otherwise responds to it.' [5]

[1] The terms parameter and measurand are variously used throughout the literature. The term parameter will be used throughout the remainder of this paper.

Using these definitions, the output from a transducer is used as input to a sensor that can use the data/information from the transducer (or multiple transducers) to perform a range of functions; from simple reporting to complex control.

It is important to note that the actual output of a transducer has limited utility until it is put into context (e.g. calibrated). That is, it is typically the output of the sensor, not the transducer, which is used as a source of information for decisions, control or visualisation. Throughout this paper, we delineate the transducer from the combined sensor (and system), with the latter being referred to as the sensor-system, or just sensor.

1.2.1 Early Sensing and Defining Traditional Sensors

Throughout history, humankind has discovered, or invented, methods to sense and qualitatively or quantitatively describe our physical surroundings, such as wind and rain. The Romans are known to have utilised windsocks for transduction and sensing purposes as far back as one hundred and five AD [6]; though windsocks originated much earlier in China and Japan [7] and may well have been used as sensors even then. The Romans used the equivalent of windsocks as both a military ensign and way to gauge wind direction and speed, a system that is still in use today at airports and high wind areas.

Another example of an early sensor system was that of the Anemometer. In 1450, Leon Alberti is said to have invented the first Anemometer, which consisted of a disk placed perpendicular to the wind that rotated when the wind was present. The speed of rotation was used as the measurable parameter for the wind speed, with a 'wind vane' being used for direction [8, 9]. While the anemometer has been refined several times throughout history, its basic principles are still used today for weather stations, albeit that they are more sensitive and accurate now through the use of modern electronics and signal processing.

The utility of electrical transduction was realised early in the development of electrical systems, with the first electrically based sensors evolving around the transduction of single-parameter physical phenomena such as heat, light, pressure, radiation, magnetism and sound. These sensors generally worked on the production of electrical signals from either simple electro-mechanical or electro-resistivity properties. The application of the known sensitivity of electrical resistance to temperature by Wilhelm von Siemens in 1860 to develop a temperature sensor based on copper is perhaps the first recorded instance of an electrical-based sensor [10]. Development of multiple sensors based on the electrical transduction of other physical parameters followed [10, 11]. In the early 20th century the first use of radio energy transduction to detect the return time of radio signals, and transduce these into an electrical signal that could be detected on an oscilloscope, produced the first usable radar sensor [12].

Within this paper, we define the measurement of a single physical parameter at a single point in time and space, such as the examples presented above, to be Traditional Sensors (TS). Furthermore, we will use this as a baseline for the broader discussion of traditional and non-traditional sensing that follows.

1.2.2 The Development of Modern Sensors

Materials processing developments and technologies in the 20th century resulted in sensors that provided greater sensitivity and bandwidth (e.g. silicon, barium titanate, gallium nitride), while advances in micro-processing provided sensor size and cost reductions [4, 13, 14]. The increased packing density and sensitivities provided by these materials and microfabrication advances enabled another major step in sensing; transducer arraying. Transducer arraying allowed data from more than one transducer to be utilised simultaneously through multiplexing, such as used in sonar arrays, phased-array radars and imaging cameras [5, 6].

Meanwhile, the utility and flexibility of the electrical transduction of signals ensured their dominance throughout the 20th century [15]. Indeed, the development of large-scale silicon processing in the 1980s heralded a new era in sensor development. Silicon was found to be suitable for transduction of a wide range of physical phenomena into an electrical output while also typically increasing the stability and reducing the size and cost of these sensors [6, 12, 13, 16].

Materials processing and microfabrication developments throughout the 20th Century also enabled the development of the digital microprocessor. Not only did digital processing increase the efficacy of existing sensors, it provided the speed and flexibility to unlock new sensor techniques and paradigms, such as multi-point sensing (e.g. transducer arraying) and multi-parameter sensing that were unrealisable (or theoretical only) beforehand [12]. Indeed, advanced sensor techniques such as hyperspectral imaging (HSI), synthetic aperture radar (SAR) and global-positioning system (GPS) simply could not have been realistically realised without digital processing [11, 17, 18].

While materials fabrication and miniaturisation of sensors led to significant improvements in single-parameter sensors, it was the advent of digital processing that provided the most significant advances in sensor utility in the 20th century: allowing more (and higher level) information to be extracted, stored and processed from the raw sensor feed and driving the natural evolution toward more complex sensor-systems. Digital processing allowed higher-level information (or understanding) to be obtained – or inferred – through the use of data processing in the back-end sensor system attached to the transducer(s).

An illustrative example of this evolution can be seen in the historical advances in radar systems, as illustrated in

Figure 1. Early pulsed radars were relatively simple, using minimal electronic processing of the transducer signal and using the human brain as the signal processor. A cathode-ray tube was used to display the radar signal return time (calibrated to distance) as the Y-axis of the cathode ray tube display, while the X-axis was connected to a time-base generator that swept the spot across the display, matched to the pulse repetition frequency of the radar [19]. These early radars provided an indication of the distance from the sensor only, with the direction (and hence position) being provided by manual alignment or dead-reckoning. There was no indication, other than what an operator might intuitively infer, of target kinematics such as velocity, manoeuvre or height.

Subsequent improvements to radar sensor-systems allowed increasingly more information regarding scanned objects to be measured (or at least inferred) by the system from the received data. As can be seen in

Figure 1, a number of the most significant improvements made to radar have occurred as a result of digital processors and processing, including developing and improving ways to measure (or infer) higher-level information constructs from the transducer signal. This includes altitude, velocity, acceleration, synthetic imaging and even target ID.

Arguably one of the most significant improvements to radar has been the development of Active Electronic Scanned Array (AESA) radars [18]. Combining the strengths of both digital processing and transducer arraying, advanced AESA radars offer capabilities that simply cannot be matched by earlier radar systems [20] including: electronic steering; multiple simultaneous beams; pulse-to-pulse frequency- and spatial-agility; per target power management; and waveform flexibility. AESA radars are recognised as one of the major challenges to, and developmental drivers for, future electronic warfare systems. Notably, electronic warfare systems are themselves critically enabled by digital processing and, increasingly, distributed transducers.

Just as with radar, as many other advanced sensors developed over time there has been a movement towards the aggregation of multiple transducer inputs. This is natural, since multiple transducers provide multiple benefits to the sensor including, improved signal-to-noise performance – and hence sensitivity – transducer redundancy and spatial discrimination. These benefits, in turn, provide better object discrimination performance to the sensor.

It is this quest for increased object discrimination that inexorably led to one of the next major paradigm advances in sensor development, which we will discuss in the next section.

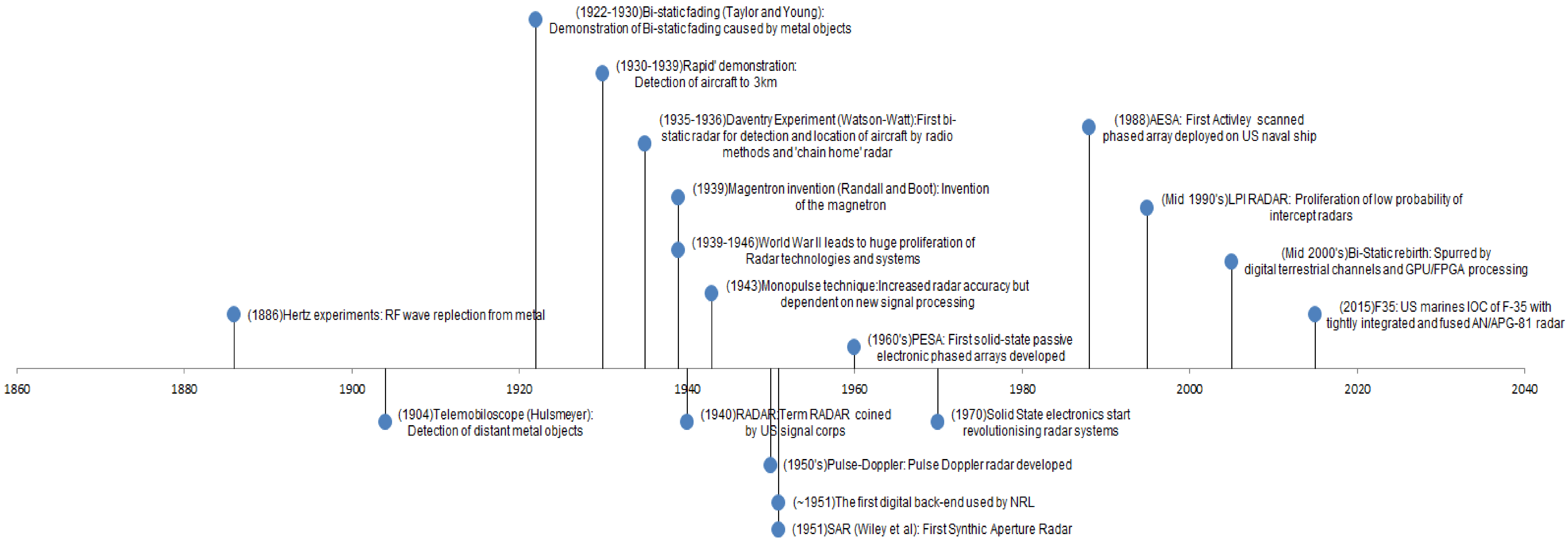

Figure 1: Some major historical radar system developments

1.2.3 The Continuing Sensor Evolution

Object/target discrimination is a primary driver for military sensor applications as it plays a critical role in any engagement: from the ability to unambiguously identify a contact by satisfying the so-called 'rules of engagement' to enabling weapons-quality targeting.

While aggregation of multiple transducers helps to improve sensor performance, it is ultimately performance-limited insomuch as it is constrained by the physical boundaries of the sensor and the physical parameter the sensor is measuring. For sensors to continue to provide ever-greater object discrimination they need to grow past the confines of single platform systems. They need to incorporate data from a wider range of transducers and include a wider spatial distribution of transducers.

Distributed sensors offer significant advantages over single sensor systems. In general, single sensors generally suffer from [21]:

1. *Sensor Deprivation (including interference):* The loss of the sensor results in a loss of perception of the measurable parameter. This includes both intentional and unintentional interference.

2. *Limited spatial and temporal coverage:* A single sensor will only measure in a small region and may give an incorrect assessment of the measurable parameter in the entire area. A single sensor will also typically have a particular acquisition time or update rate, which will limit the frequency of measurement.

3. *Accuracy and Precision:* Both the accuracy and precision of the measurable parameter output is limited to the precision of the single sensor system making the measurement.

Distributed sensor networks help resolve many of single sensor issues, including [21]:

- *Reduced Sensor Deprivation (including interference):* Distributed sensors overcome the deprivation issue by utilising multiple sensors and implementing fault-tolerance logic which provides redundancy. In addition, sensor systems that utilise different sensor types are also more tolerant to interference.

- *Increased spatial and temporal coverage:* Additional sensors allow sensing to be undertaken in multiple locations and at differential times to overcome sensor lag; so that one sensor may be acquiring data while another may be preparing to acquire data.

- *Improved Accuracy and Precision:* The measurable parameter is available from multiple positions for confirmation and improved precision and resolution. The availability of multiple measured values may be used to increase measurement precision (that is, reduce uncertainty).

In general, distributed single-parameter sensors may improve the precision, reliability, spatial and temporal coverage of a parameter. That is, a performance improvement is gained from aggregating sensor data (or information derived from sensor data) such that the resulting information is in some sense better than would be possible when these sources are used individually [21, 22]. However, it should be noted that while the aggregation of single-parameter sensors provides for increased sensor performance, in general these performance increases are not as great as those obtained from the aggregation of multiple transducers in a single sensor. Regardless, distributed sensors provide significant capability, performance and architectural flexibility increases compared with their non-distributed counterparts.

In addition to aggregating single-parameter sensor outputs, distributed sensors allow multiple sensor outputs to be aggregated in distributed multi-parameter sensor systems. The aggregation of multiple sensor data, commonly known as 'sensor fusion' [22, 23] helps to reduce sensor deprivation while providing potential increases in distributed sensor-system performance, including spatial and temporal coverage, accuracy and precision. Appropriate sensor-fusion processes provide the potential for improving parameter measurement accuracy while not changing the original distributed sensors. As a result, any improvement or development in sensor materials or manufacturing techniques that result in improved sensors should ultimately also result in improved sensor-systems when utilising networked sensor and information fusion. This increased performance is driving the trend towards increased data and information fusion in sensors.

1.2.4 Fusion

In 1991, White proposed a definition of data fusion to be:

> ...a process dealing with the association, correlation and combination of data and information from single and multiple sources to achieve refined position and identity estimates... [22].

The rapid advancements in technology in the late twentieth century saw a shift from traditional processing of data from a single sensor to fusing the data from multiple sensors. This paradigm shift redefined data fusion to be viewed as processes of correlating and combining data and information from *multiple* sensors and associating information from databases and other sources. Further advances in technology and data fusion techniques not only improved the accuracy of data fusion, but also the emergence of real-time fusion.

Hall and Linas [24] asserted that the data fusion process involves a hierarchical data transformation: data fusion begins with observed parameters to obtain the kinematics of an entity and concludes with the contextual interpretation of the entity, based on the environment and relationship between other entities. This view is supported by the Joint Directors of Laboratories (JDL) who proposed the most widely accepted model which conceptualises and identifies the processes, functions and techniques that are necessary in data fusion. The preliminary JDL model consisted of three levels of data fusion: sensing, situation assessment and threat assessment.

The JDL Data Fusion model was revised by [25], which is commonly referred to as the 1992 Version of data fusion. This revision includes a newly-developed fourth level of data fusion, as well as amendments to the first three [23] [26], which were renamed to Object

Refinement, Situation Refinement and Threat Refinement. The new fourth level was labelled Process Refinement. Shahbazian [26] defines this level as a meta-process, where the real-time performance of data fusion is monitored and where information that can improve multi-level fusion are identified. An update of the 1992 version was initiated in 1998 by Steinberg et al. [27], which is the current and most widely accepted version of the data fusion model. Each level needs to ensure the ability to i) be able to represent a variety of problems that are solved using different techniques and ii) maintain consistency. Therefore, Steinberg et al. [28] propose that instead of four fusion levels, there are actually five, and each level needs to be rephrased from earlier versions of the JDL data fusion model:

- Level 0 — Sub-object assessment (source pre-processing): estimates and predicts observable states from signals and/or objects. Steinberg et al. [29] believe this level is not concerned with the entities, but rather measurements.
- Level 1 — Object Assessment (object refinement): estimates and predicts the states of entities based on their observation to track association and continuous and discrete state estimations (i.e. kinematics, target type, combat ID). This level is concerned with associating entities with identity, classification, attributes, activities, locations and dynamics.
- Level 2 — Situation Assessment: addresses the interpretation of data the same way a human interprets sensor data. By examining this statement, Situation Assessment focuses on manipulating relational information to obtain the meaning of a group, or collection of entities.
- Level 3 — Impact Assessment: estimations and predictions of the effects from participant, or user actions.
- Level 4 — Process Refinement: utilises resource and sensor management and data acquisition to support mission objectives, where processes and fusion performance are refined. Process refinement needs to consider real-time control, long-term performance, the size and quality of information that is being produced.

Error! Reference source not found. illustrates this new version of the JDL data fusion model.

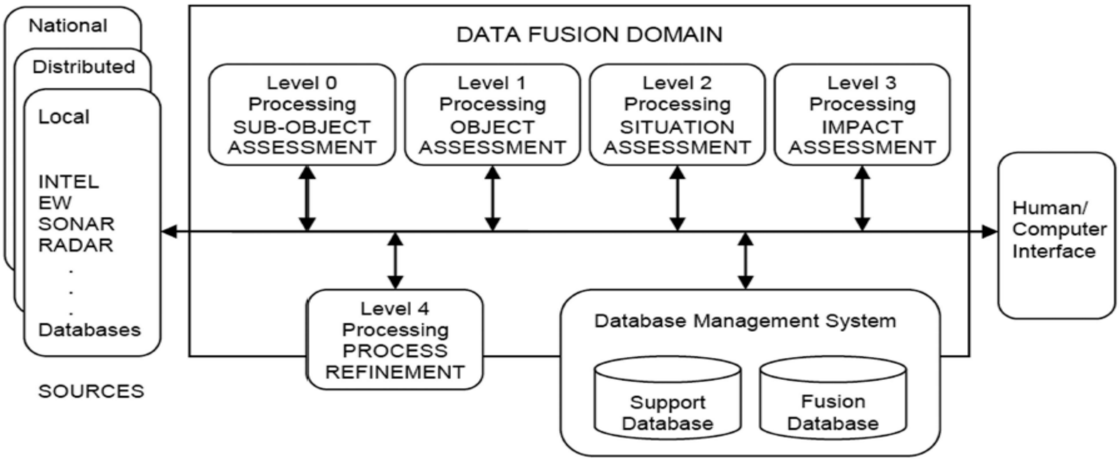

Figure 2: The proposed five level JDL fusion model.

Interestingly, Hall and Linas [24] believe the data fusion process must possess inference, or reasoning. This addition to the data fusion process is viewed not as pure data fusion, but rather the concept of Information Fusion (IF).

The concept of information fusion relates to incorporating and establishing inference, decision making and situational assessment within data fusion systems [30], [31], [32]. Roy et al. [30] argue that information fusion is responsible for:

- Extended spatial and temporal reporting which will improve confidence and entity detection and decrease ambiguity.
- Managing vast amounts of uncertain information to form a coherent and representative situation for decision-making.
- Assisting in dealing with complexity and uncertainties in dynamic environments.

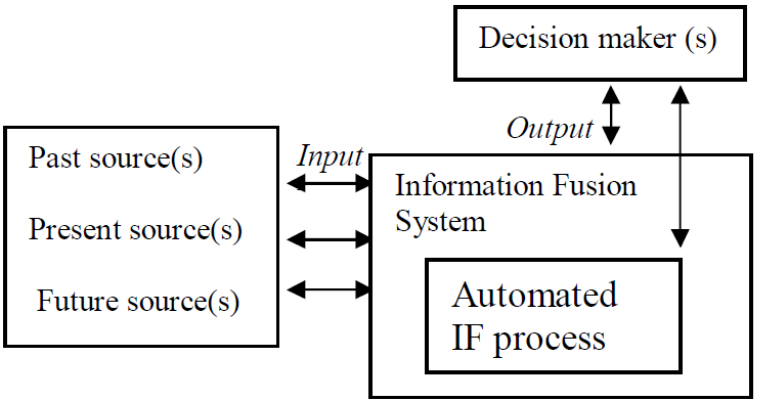

Figure 3: Information fusion in the decision process [1].

There is still arguably significant debate regarding the delineation of data and information fusion. Many argue that data fusion and information fusion are the same, or interchangeable, however Steinberg et al. suggest that data fusion and information fusion are actually *mutually exclusive [29]*. Appriou et al. [33] and Wark and Roy [34] contend that the fusion process for information fusion fundamentally differs from data fusion. However, others believe that fusion is dependent on the information from the organic data processed within data fusion.

While both data fusion and information fusion require an understanding of the environment and its information sources, [33] and [34] suggest the difference between information fusion and data fusion is that the former needs to possess an appreciation to the application of the information, requires life cycle support and the design of an information fusion system is more involved than data fusion. This is because information fusion is central to a decision being made, as illustrated in Figure 3.

Blasch [35] argues that the 'user' is an integral part of a fusion system and suggests that without including the user within the model, there is no need to provide fusion of multisensory data. To support a user the fusion model must support the basic cognitive activities, in particular knowledge representation and reasoning. Without these two basic cognitive functions, inference and decision-making cannot occur. Blasch has proposed the addition of a Level 5 (Cognitive/User Refinement) to the JDL model. He views Level 5 as affording '…determination of who queries information and who has access to information (e.g. information operations) and adaptive data retrieved and displayed to support cognitive decision making and actions'. Blasch [35] continues, asserting that Level 5 is where the aggregation of Levels 0-3 data gathering and the user's perception of the current social, political, and military arena occurs. The inclusion of this level turns the fusion model from resembling classical situation awareness to a more contemporary situation understanding model [36]. The difference between the two is that the latter allows the user to be aware of, estimate, predict and prioritise events occurring within their environment.

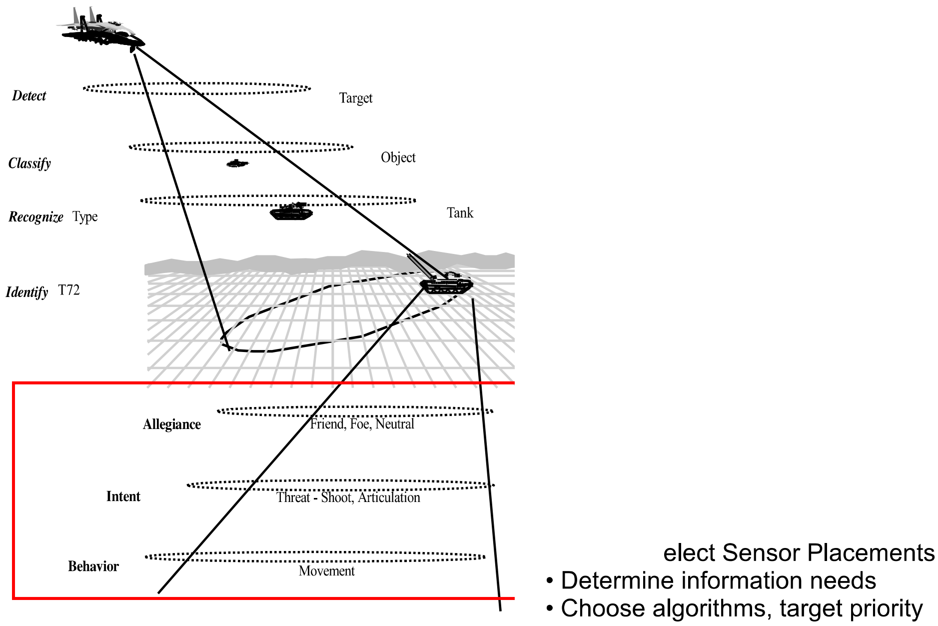

Figure 4: Target tracking as related to the Information Fusion Process levels: after Blasch et al [35].

By utilising situation understanding, Level 5 exploits knowledge representation, semantics and reasoning, therefore promoting the delivery and display of knowledge, creation of a mental model and representation of the current situation, as well as decision-making. Instead of being a consumer of the fusion process, level 5 allows the user [2]to be part of the process. An example of level 5 is illustrated in Figure 4. Instead of merely collecting data and adding context based on the current situation, cognitive refinement allows the user to add value, priority, context and intent. In the case illustrated in Figure 4, a user is able to explore the allegiance (value), intention of the target (priority and context) and other ambiguous behaviours (intent) a target is exhibiting. In addition, this extension of the classical data and information fusion process is the enabler for a more distributed and shared fusion process amongst a group of users.

[2] A user can human or machine.

2. What is a Non-Traditional Sensor?

While it appears to be straightforward to define Traditional Sensing (TS), it is not so trivial to define Non-Traditional sensing (NTS) and, indeed, the difference between these two. Borbath [37] suggests that NTS is difficult to standardise and argues that the ability to distinguish a traditional sensor from a non-traditional sensor also depends on the context and indeed the organisation considering it. That is, one organisation's NTS could be considered another organisation's TS. Furthermore, in most cases, the delineation of TS from NTS is made based on the entity utilising the sensor(s) or data provided. Borbath further proposes a framework for the definition of TS and NTS systems, as shown in Table 1.

A hyperspectral remote sensor is an imaging sensor that collects images for hundreds of contiguous narrow wavelength ranges. Essentially conducting a spatial scan of reflectance as a function of wavelength, to build a multi-wavelength representation of an area. It is typically represented as a so-called three-dimensional hyperspectral data cube [38]. These data cubes can then be processed on a pixel-by-pixel basis to identify spectral signatures for material and object identification [38, 39].

However, while the concept of hyperspectral imaging was first proposed in 1985 by Goetz [20], in essence the hyperspectral system utilises a photo-spectrometer to distinguish fundamental optical features as a function of wavelength. This underlying sensing technique has been utilised as far back as 1868 by Pierre J. C. Janssen [3], to observe the spectrum of the sun. Hyperspectral imaging logically extends the core photo-spectrometer concept to that of an imaging sensor array, with a photo-spectral array. This transducer array is coupled to a back-end hardware and software processing system and, together, they comprise the hyperspectral sensor-system.

Table 1: Traditional Sensing and Non-Traditional Sensing Definitions

Traditional Sensing (TS)	Non-Traditional Sensing (NTS)
Built for purpose	Built primarily for other purposes
Intentionally connected to a public or private network for data collection	Connected to a network but accessed by non-primary actors
Controlled and maintained by the owner or agent of the sensor system	Not owned or maintained by the non-primary actors
Having achieved a mature, stable utility in an established architecture	Inherently adaptable to novel applications and may not be mature or stable

When considered in this way, several questions naturally arise. Firstly, 'How non-traditional is hyperspectral imaging?'

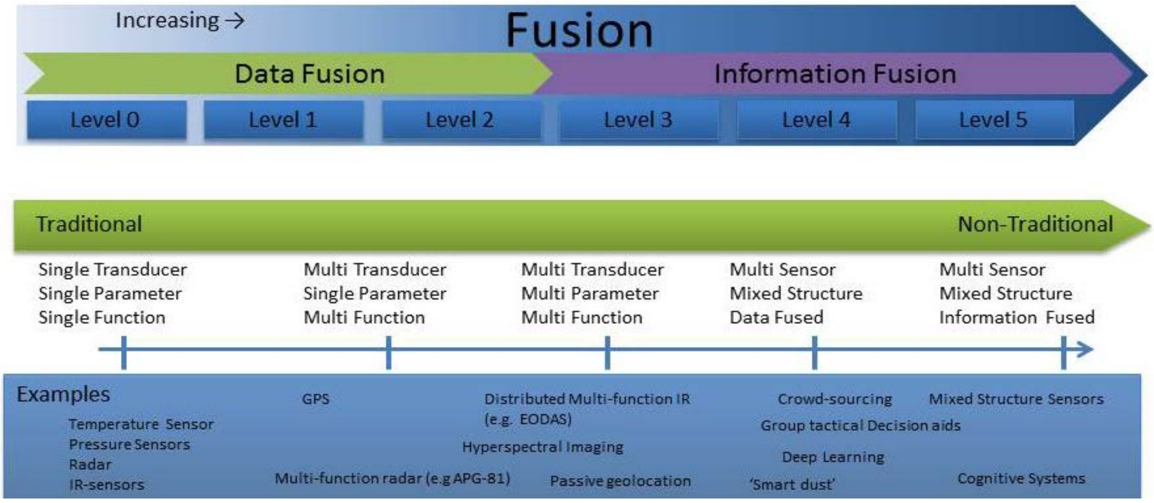

Figure 5: Defining traditional and non-traditional sensors as a spectrum.

While it is clear that hyperspectral imaging provides increased information discovery and new possibilities for object discrimination, it is also clearly a logical extension of a traditional and well-understood sensing technique. Hyperspectral images could be formed by scanning a single-point photo-spectrometer: in fact, the first fielded hyperspectral imager AVIRIS [40] used point-wise raster scanning [17] of a photo-spectrometer.

The second question we may ask is 'How are the majority of the new capabilities that we attribute to hyperspectral imaging realised?'

Even a cursory analysis reveals that it is in the aggregation and fusion of the data from the transducer array where the capabilities that have come to define the utility of hyperspectral sensing are realised. Goetz himself wrote [41]:

> Progress required developments in electronics, computing and software throughout the 1980's and into the 1990's before a larger segment of the Earth observation community would embrace the technique.

Let us consider two other sensor techniques that are sometimes referred to as NTS in military circles; namely Synthetic Aperture Radar (SAR) [42] and Synthetic Aperture Sonar (SAS) [43]. It may seem sensible to relate both sensing systems as non-traditional. However, it becomes less evident when one considers that, at its core, SAR actually utilises traditional radar transducers (apertures) in conjunction with advanced signal processing to realise the SAR capabilities. Similarly, SAS systems typically utilise established sonar transducers and leverage on advanced signal processing to produce the synthetic imagery associated with SAS [15]. Furthermore, bats utilise echolocation to produce acoustic imaging similar to that of SAS [44]. Does this mean that bats are using a non-traditional sensing system?

It is clear from the above that the framework proposed by Borbath is both inadequate, rather subjective and lacks granularity. A clearer method for defining and categorising sensing systems as Traditional or Non-Traditional Sensing systems is needed.

3. Defining TS and NTS using the Information Fusion Spectrum

The ever-increasing complexity of sensor-systems brings with it an increasing need for data, data aggregation and fusion. Indeed, as discussed in the previous sections, it is arguably the data processing, aggregation from distributed transducers/sensors, and fusion that provides the greatest increases in sensor capability and drives the development of new paradigms for sensors. Ultimately, it is also likely to be the over-riding reason that has led to the perceived need for the term non-traditional sensing.

Insomuch as we even need to define traditional and non-traditional sensing, it seems reasonable to consider categorising them by leveraging the concepts within the established information fusion framework described earlier [15].

The premise is that as a sensing-system becomes more complex (i.e. moving from a single sensor through distributed and then to multi-function and multi-parameter sensor systems) the system itself naturally moves from being 'traditional' towards being more 'non-traditional'. The schema for categorising sensing systems in this way is shown in Figure 5.

The concept naturally extends itself to multi-transducer and multi-sensor systems if we consider these systems in terms of their data/information aggregation and fusion capabilities, rather than their physical characteristics.

As an example, the AN/APG-73 that is utilised in the classic F/A-18 uses a slotted radar waveguide array and is consider to be a traditional sensor system. However, the AN/APG-81 that is utilised in the F-35, uses an AESA phased array and is considered to have NTS attributes. However, the actual transducers that enable the radar functionality for both systems are similar – albeit the APG-81 utilises many hundreds of active transmitter/receiver modules, as opposed to the single transmitter and receiver modules used in the APG-73. It is the advanced signal processing, data aggregation and fusion that is used by the APG-81 (enabled by the distributed transducers) in the F-35 Mission System that provides the significantly enhanced functionality that gives the APG-81 radar sensor more NTS-like capabilities.

The proliferation of mobile and always internet-connected devices has seen the introduction of many new sensors and sensor systems. The ability to categorise these new sensors and systems utilising the information fusion spectrum construct is valuable. That is, when a new sensor or sensor-system arises we can consider where it resides in the information hierarchy, and therefore categorise it appropriately. As an example, and as previously discussed, historically Hyperspectral sensing in the ADF has typically been classed as an NTS system. However, when considering it in the sensor fusion construct it can be considered to be an enhanced traditional sensing system since it possesses multi-transducer, single-parameter and multi-function qualities.

It is possible that the model proposed in Figure 5 will need to be extended in the future. This will be a natural result of any changes that occur to data and information fusion models as they continue to evolve. Possible changes may include the extension of the fusion model to better capture advanced machine teaming concepts that differ from human teaming concepts and 'hyper-cognition', in which machine-learning and big-data constructs are effectively leveraged to provide predictive analysis beyond what humans are capable of today. This is not a failure of the model; rather it is simply an acknowledgement that the framework is simply a reflection of the JDL fusion model.

4. Information as a Sensor

There has been a proliferation of sensors and sensor-systems that has accelerated over the last two decades. Primarily driven by the consumer mobile market and the desire for interconnected lifestyle, this proliferation has produced not only cheaper sensors, but a data-rich sensor environment. This 'Internet of Things' (IoT) [45] potentially allows any device connected to the internet to act as a sensor. These sensors produce an abundant amount of information such as text, voice, images, video and location which, due to the nature of the devices that integrate these sensors, are distributable and aggregable.

It is estimated that by 2020, 50 billion devices will be connected to the internet. This is driven heavily by commercial industry and is creating a ubiquitous, distributed and mobile sensing paradigm. The amount of data/information generated and transferred across networks in these environments is enormous. Much effort in the commercial sector has been directed towards the benefits of accessing and processing this data/information for varying and diverse applications [38, 46].

An example of this is the WAZE [2, 47] application. While described as a turn-by-turn navigation system, WAZE diverges significantly from the traditional GPS in that it is community (or crowd-source) enabled; gathering complementary map data and traffic information from its users.[3] In addition to providing real-time traffic and routeing updates, it also allows users to report multiple types of information, such as accidents, traffic jams, fuel prices, mobile traffic radars and many others [3]. These information services are only possible due to the data analytics that are being constantly applied across the mass amount of data and information produced by the Waze 'sensor' network. These sensors range from GPS to text and even human cognitive 'sensors'.

While Waze is a simple concept, it is an excellent example of the utility of fusion from multiple sensors, multiple parameters and multiple functions for the production of information overlays and provision of a common operating picture.

As another example, in 2008, Google introduced a web service that used a software model that combined and utilised previous individual searches along with geographic data regarding the origin of those searches, to understand and model the spread of previous virus outbreaks. This information was then applied to a new virus outbreak to model the

[3] Both Apple and Google (whom acquired WAZE in 2013) now incorporate similar crowd-sourcing constructs in their own mapping applications.

expected spread; with their initial results being able to, in near real-time, accurately predict the spread of the virus [48]. While Google Flu Trends is now deactivated, others have extended the approach by application of a learning model to account for changing search behaviours while also incorporating other sources of data from social media, such as twitter and Facebook to undertake the fusion process [17, 47].

This particular example, one of many, demonstrates the utility of analytics applied to structured and unstructured 'big data'. In this situation, the analytics are being applied to unstructured information using a semantic fusion process. Referring back to Figure 5, we can see how this type of sensor-system takes us naturally further along the Non-Traditional sensing spectrum and towards cognitive systems.

Both WAZE and Google Flu Trends provide examples of a consistent trend. A trend in which data (or indeed information) itself has become a sensor. This is the concept of Information as a Sensor. This paradigm will continue to expand as machine intelligence, autonomous, behavioural and, indeed, cognitive systems continue to evolve and be realised. The concept of Information as a Sensor (IaaS), including drivers, benefits, issues, and potential uses will be covered in depth a separate report.

5. Closing Remarks

For centuries humankind has been developing transducers and sensor-systems to measure and understand the environment in which it resides. Over time these have evolved and increased in complexity so as to improve their performance; be it increasing speed, accuracy, reliability, precision or sensitivity. While many of these improvements were initially gained through materials fabrication and miniaturisation of sensors, the advent of digital processing in the second half of the twentieth century provided arguably the most significant evolution toward more complete and complex sensor-systems. Digital signal processing has allowed higher-level information to be gained via data processing in the back-end of the sensor-system and has allowed the seamless integration of multiple transducers and sensors in distributed multi-parameter systems. The aggregation and/or fusion of multiple transducer and sensor data provided further increases in sensor-system performance, including: spatial and temporal coverage; accuracy; and precision, while also helping to reduce sensor deprivation.

While the term 'non-traditional sensing' (NTS) has somewhat recently gained popularity within military circles, the definition of NTS is somewhat ambiguous. Attempts by other authors to provide a definitive method for identifying a sensor or sensor system as TS or NTS appear incomplete and, in some cases, make the classification either ambiguous or arbitrary. In an attempt to overcome this confusion, it is proposed to recast our thoughts about how a 'non-traditional' sensor is classified by utilising the established JDL fusion framework. The principle being that, as a sensor (sensor-system) becomes more complex the system itself naturally moves up the JDL fusion 'spectrum' and, in doing so moves closer towards being a more so-called NTS system.

In fact, this raises the question of whether the term Non-Traditional Sensing (NTS) is itself a misleading term, since it is not so much the sensors that are non-traditional but rather the layering of multiple sensor inputs, data/information aggregation and fusion that provides the non-traditional characteristics of these sensor-systems.

With the explosion of always-connected devices in the emerging Internet of Things (IoT), almost any device connected to the internet now has the potential to act as a sensor. This proliferation has produced a data-rich sensor environment and an abundant amount of potential information, which is both distributable and aggregable. The utility of applying analytics on this 'big data' (which consists of both structured and unstructured information) in a semantic fusion process has been proven to substantially increase the effectiveness of supplied sensor data/information. As this trend continues, spurred on by the global proliferation of smart devices and cloud computing services, these sensor-systems will produce an expanding abundance of contextual information – such as text, voice, images and video; mobile, aggregated and geo-located by GPS, WiFi, IP or image analysis and driven by the consumer demand for location-based information services. The utility of machine-to-machine communications, machine learning and big-data techniques on this data will take us naturally further along the information fusion spectrum and towards cognitive-based inferencing systems.

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DEFENCE SCIENCE AND TECHNOLOGY GROUP DOCUMENT CONTROL DATA	1. DLM/CAVEAT (OF DOCUMENT)

2. TITLE	3. SECURITY CLASSIFICATION (FOR UNCLASSIFIED LIMITED RELEASE USE (U/L) NEXT TO DOCUMENT CLASSIFICATION)
Expressing Sensor Maturity in Terms of Information Fusion: Re-defining Non-Traditional Sensing	Document (U) Title (U) Abstract (U)
4. AUTHOR(S)	5. CORPORATE AUTHOR
Jayson Priest, Timothy Priest and Angela Consoli	Defence Science and Technology Group PO Box 1500 Edinburgh SA 5111

6a. DST GROUP NUMBER	6b. AR NUMBER	6c. TYPE OF REPORT	7. DOCUMENT DATE
DST-Group-TR-3400	AR-016-953	Technical Report	August 2017

8. OBJECTIVE ID	9.TASK NUMBER	10.TASK SPONSOR
	JNT 07/398	N/A

11. MSTC	12. STC
Strategic Capability Analysis	Technology Futures and Forecasting
13. DOWNGRADING/DELIMITING INSTRUCTIONS	14. RELEASE AUTHORITY
	Chief, Joint and Operations Analysis Division

15. SECONDARY RELEASE STATEMENT OF THIS DOCUMENT

Approved for public release.

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Non-traditional, sensing, fusion, service.

19. ABSTRACT

In recent years, the term ‘non-traditional sensing’, or NTS, has seen increased usage; particularly within military parlance. This paper explores the definition of NTS, some of the technologies that are typically associated with NTS and, ultimately, questions the need for NTS as a concept. Instead, it suggests that NTS is really an artefact of perception resulting from the natural and ongoing development of sensor systems towards higher levels of data and information fusion. A light-weight model that provides a generalised mapping between increasing sensor complexity and fusion is presented as an alternative to more formal models that have been proposed previously.