

Communication Network Awareness Machine System Phase I Development: The Intelligent Party-Line Schema

Vincent E. Houston
Crew Systems and Aviation Operations Branch
NASA Langley Research Center
Hampton, Virginia
vincent.e.houston@nasa.gov

Bryan A. Barrows
Autonomous Integrated Systems Branch
NASA Langley Research Center
Hampton, Virginia
bryan.barrows@nasa.gov

Abstract - As NextGen continues toward the full implementation of a Net-Centric Architecture (N-CA) it will inherently provide a continuous increase to the Four-Vs components (Volume, Velocity, Value, and Variety) of big data. This will create an insurmountable environment for direct-action aviation personnel (DAAP) as the DAAP's natural abilities to manage and process data into actionable information will be overmatched by the Three-Vs. Therefore, conducting operations within a N-CA requires that new tools and applications be researched and developed to aid the DAAP's ability to understand and manage data, mitigate non-normals, and create contingency plans and actions. This paper describes a research area at NASA Langley Research Center known as the Intelligent Party-Line (IPL).

Keywords - *Intelligent Party-Line, Communication Network Awareness Machine System, Autonomously Triggered Native Language Translator, Traffic Data Manager, Net-Centric Architecture*

I. INTRODUCTION

The future urban airspace community (UAC), within the National Airspace System (NAS), is characterized as being a densely populated, operationally rich environment, designed to accommodate a variety of manned and unmanned air vehicles facilitating multiple delivery services. Safe, effective, and efficient operational capabilities will have to be inherent to any air vehicle operating within the NAS. However, due to the fundamental characteristics of NextGen's Net-Centric Architecture (N-CA)[1] it is evident that tools, applications, and procedures, using burgeoning technologies such as Statistical and Machine Learning techniques need to be developed. The development of these technologies will provide sufficient aid to direct-action aviation

personnel (DAAP) situation awareness, particularly within the area of aviation communication. For DAAP to aviate safely, effectively, and efficiently, within a Next-Gen N-CA, it is paramount that data inherent to that environment be transformed immediately to actionable communication data (information). The need to transform communication data into information is not unique to operations within the NAS. However, with the addition of big data's Three-Vs (Volume, Velocity, and Variety)[2] into the N-CA data stream, a new operating paradigm will be needed in order to maintain current day safety and efficiency.

This paper describes the schema for the Intelligent Party-Line (IPL)[3] functionality being developed by NASA Langley researchers. The IPL is being designed to address the technical challenge of UAM's contingency and mitigation management operations in the UAC via the integration of autonomous communication capabilities.

II. BACKGROUND

An overview and the main technology of IPL will be described in the following sections.

A. Communication Network Awareness Machine System (C-NAMS)

C-NAMS[4] is a self-contained Increasingly Autonomous System (IAS) designed to ingest, repose, and transmit data from NextGen's N-CA to Intelligent Machine Agents (IMAs) designated to conduct specific aviation tasks.

Configured with a real-time streaming data architecture and a multimodal data repository, C-NAMS facilitates the ability of the DAAP to easily interpret large amounts of data. This will support the DAAPs in the overall mission to safely aviate,

navigate, and communicate within the UAC. An amalgamation of IMAs, integrated within C-NAMS, leverages the full complement of ingested data, refining it into actionable information. C-NAMS IMAs extend to the DAAP's capacity to operate in the UAC without loss of situation awareness, thereby building trust and a symbiotic relationship between human and machine agents. Figure 1 depicts C-NAMS component architecture.

The real-time data architecture (RTDA) is the technological corner stone enabling the Machine System to provide awareness to the DAAP by delivering correct, timely, and relevant information. This matches the proliferation of big data's Three-Vs, thus enabling the DAAP understand the operating environment with a reasonable workload. An additional benefit of an RTDA is the prevention of a "too late data architecture," meaning mistimed data

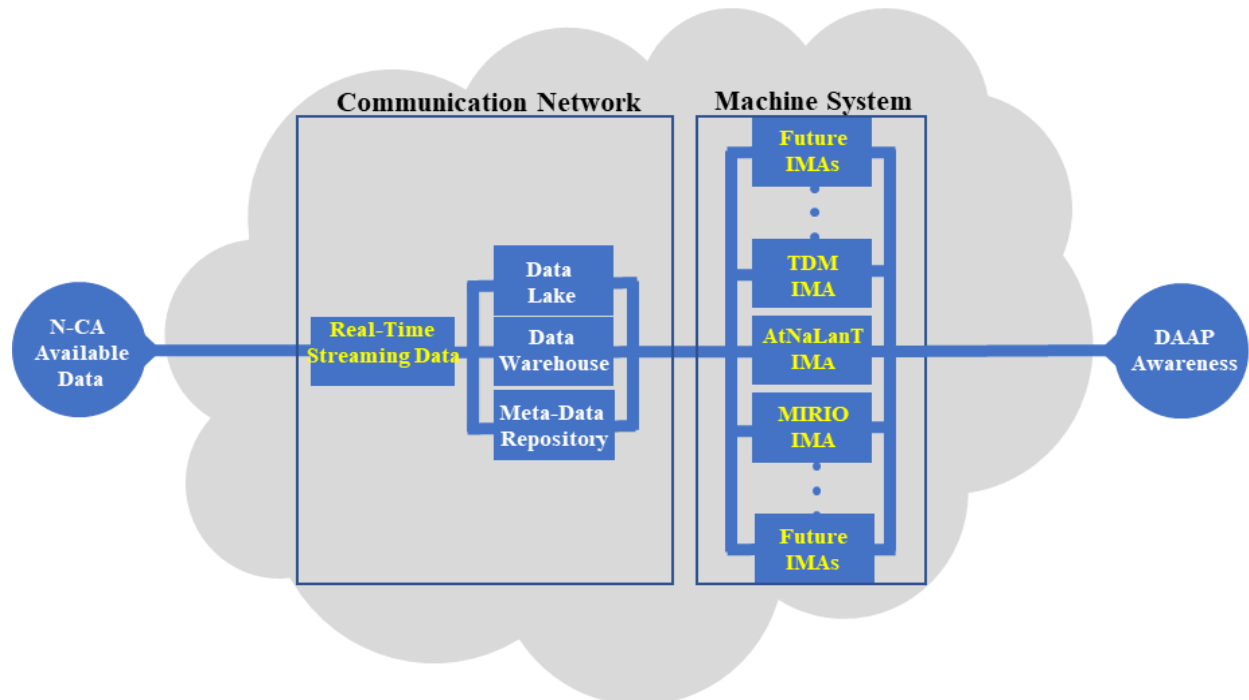


Figure 1. Communication Network Awareness Machine System. Credit: NASA

The following list provides the description of C-NAMS integral components that allow the IPL functionality.

a.) Real-Time Streaming Data Architecture: Fundamental to the system's Communication Network is its ability to stream, ingest, and process data. This allows the execution of real-time data analytics by C-NAMS's Machine System.

would cause risk management procedures to be ineffective and the IPL would be unreliable.

The RTDA is comprised of several Apache Software Foundation (ASF) frameworks: Apache Spark (*a unified analytics engine*)[5], Apache Kafka (*stream-processing software bus*)[6], and Apache Hadoop (*big data distributed storage and processing*)[7]. Figure 2 illustrates the RTDA pipeline.

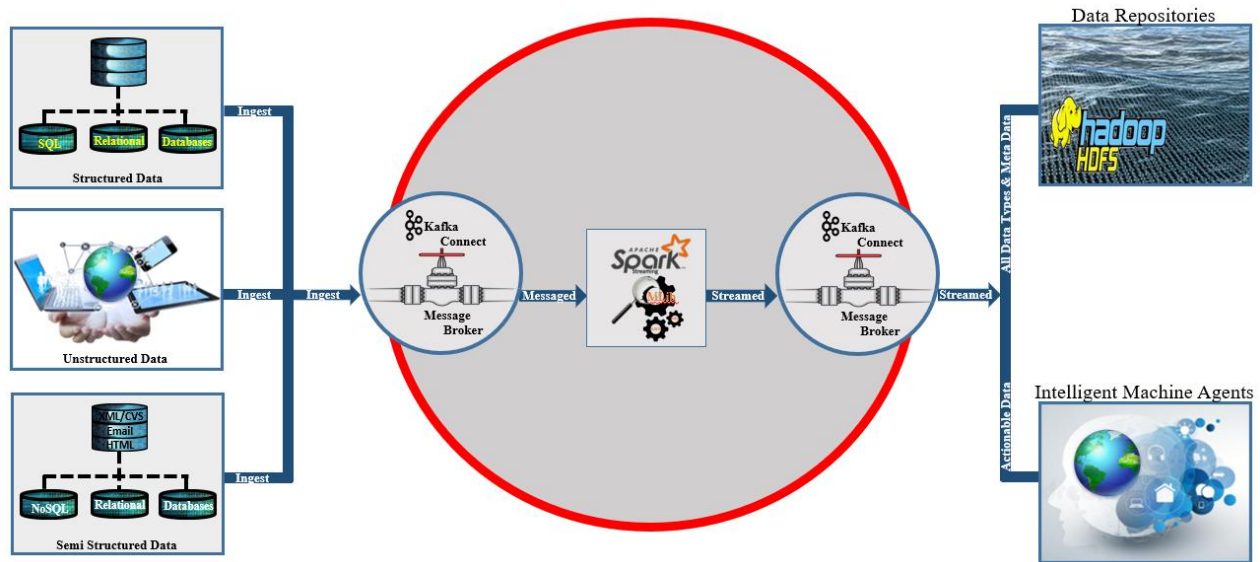


Figure 2. Real-Time Data Pipeline Big-Data Kappa Architecture. Credit: NASA

The rationale behind the use of ASF frameworks (Hadoop, Kafka, and Spark) is the need for the RTDA to encompass the following list of big data pipeline characteristics: (1) Big Data Compatibility, (2) Glass-to-Glass Latency of less than five seconds, (3) Scalability, (4) Flexibility, (5) Efficiency, (6) Use-Case Diversity, and (7) programming language independence. The core processes for the RTDA are messaging and data ingestion. The role each Apache platform in the RTDA's structure is described below.

Apache Hadoop – This platform is the foundation for the Apache Spark and Kafka frameworks. The persistent data storage and robust security are accomplished via the Hadoop Distributed Filesystem. C-NAMS's multimodal data repositories are derived from Hadoop distributing large amounts of ingested data into three different repository categories: 1) batch data (*data warehouse*), 2) immediate actionable data (*data lake*), and 3) metadata (*data mart*). The main implementation of Apache Hadoop with respect to C-NAMS's RTDA is to allow for historical data uses and for near-real-time IMA training and testing.

Apache Kafka – The Kafka platform serves as RTDA's messaging system and is the entry point for N-CA ingested data. Utilizing two architecture elements of Apache Kafka (*Producer and Subscriber*), along with priority queuing, allows the RTDA to write data to a producer and send that data to a listener. The use of Apache Kafka allows the RTDA to achieve unified, high-volume, high-velocity real-time data feeds.

Apache Spark - The Spark platform acts as the subscribed listener to the RTDA's messaging system and provides its real-time capabilities. The Apache Spark uses Spark Core's fast scheduling so that stream analytics can be conducted.

Instituting a real-time streaming data pipeline allows for one of two different architectures: Lambda and Kappa [8]. The Lambda architecture allows the querying of data to be accomplished both in real-time and batch modes. However, the Kappa architecture offers the same technological stack to handle both real-time stream processing and historical data processing, but with a smaller footprint i.e., *two layers instead of three* and with a simpler implementation. Therefore, the Kappa architecture (using virtual nodes) was implemented for C-NAMS's RTDA without the loss of historical data and maintaining its ability to perform large scale analytics. The Kappa architecture consists of a Real-Time/Streaming layer (Kafka) and the Servicing Layer (Spark).

b.) Traffic Data Manager: The Traffic Data Manager (TDM) is an increasingly autonomous system utilizing machine learning (ML) algorithms and subject matter expert (SME) knowledge transfer in order to provide the DAAP with visual air traffic information.

Utilizing C-NAMS's RTDA, TDM's daughter-technology, the Dynamic Air Traffic Application

(DATA) filters the following TDM prediction model state data: *traffic position (latitude and longitude), course, airspeed, altitude, altitude rate, range, and bearing*.

Currently, the TDM implements a Multi-View Ensemble Learning (MVEL) data analysis and machine learning methodology, which takes a complete data set and segments into multiple distinct feature subsets. These subsets incorporate various predictors from the data set to enable a target concept of learning for standalone supervised classifiers. TDM consists of four feature subsets and four different classifying algorithms [9], with the first algorithm being Bootstrap-Aggregated Decision Trees (TreeBagger). TreeBagger is based on an ensemble of decision trees for application in either classification or regression tasking. TreeBagger relies on ClassificationTree (CT) and RegressionTree (RT) functionalities to grow individual trees. CT and RT accept the random number features for each decision split as an optimal input argument [9].

The second classifying algorithm is the K-Nearest Neighbor (K-NN). K-NN is a non-parametric classification method used to assign weightings ($\mathbf{W}(i)$) to the contribution of features taken from the data subset. The following posterior probability function $p(j|X_{new})$ identifies patterns in the feature subset and infer air traffic relevance with respect to ownship. The truth of this statistical probability is derived from the representation of:

$$p(j|X_{new}) = \frac{\sum_{i \in \text{nbnd}} W(i) \cdot 1_{Y(X(i)=j)}}{\sum_{i \in \text{nbnd}} W(i)} \quad (1)$$

The Naïve Bayes classifier is a simple "probabilistic classifier". It combines an independent decision model with a common decision rule to select the hypothesis that is most likely to occur. The resulting classifier is a function that assigns a prediction $\hat{y} = C_k$ for some k such that in:

$$\hat{y} = \underset{k \in \{1, \dots, K\}}{\text{argmax}} p(C_k) \prod_{i=1}^n p(x_i | C_k) \quad (2)$$

The SVM classifier inputs training examples from the data set, marking each as belonging to either one of the three air traffic relevancy categories (relevant, maybe-relevant, not-relevant). The mathematical model that defines SVM training is:

$$P(s_j) = \frac{1}{1 + e^{(A s_j + B)}} \quad (3)$$

where A and B are the slope and intercept of the

predictors[10]. The following equation provides the new vector observation weights for the model inferences based on the largest posterior probability

$$(W_j = w_j P_j \sum_{k=1}^K C_{jk}) \quad (4)$$

where $\mathbf{P}$ represents the posterior vector, $\mathbf{C}$ is the misclassification matrix, and $\mathbf{w}$ is the observation weight vector[11].

Once the data have become part of TDM's "Supervised Learning Workflow"[4], predictions are made, meaning that knowledge is provided to the DAAP concerning relevant aircraft operating in their airspace. This autonomously provided real-time visual representation provides an intuitive visualization of the Four-Vs of big data for the DAAP.

c) Autonomously Triggered Native Language

Translator (At-NaLanT):

At-NaLanT is an IMA that is responsible for independently identifying the relevancy category of all ingested RTDA audio and textual communications, within an ownship's airspace. At-NaLanT translates and pairs those communications with the respective air vehicle. For example, an air vehicle being operated in the NAS by a flightcrew whose native language is not English, will have all of its communications identified, translated to English (both auditorily and textually) and paired to match that air vehicle on the visual display of the ownship. Conversely, English communications will be translated to a flightcrew's native language.

At-NaLanT is a critically enabling functionality for operations within the NAS organizing aircraft communication, eliminating miscommunications, and rapidly dispersing the vast influx of communication data available in a NextGen N-CA.

The At-NaLanT is comprised of its own collection of IMAs that perform Automatic Speech Recognition (ASR) and Natural Language Processing (NLP). In near-real-time, At-NaLanT currently carries out

(a) Speech-to-Text (STT), (b) Text-to-Speech (TTS), (c) aircraft call sign detection from textual transcriptions, and (d) native language translation from incoming and outgoing audio communications. It is noted that the invocation of the aforementioned operations is primarily ordered semi-sequentially, particularly concerning audio reception. However, by design, these operations can be decoupled from the ordering pattern and performed individually, providing greater flexibility and scalability to C-NAMs. Figure 3 develops AT-NaLanT's ASR and NLP ensemble pipelines. See Figure 3 for the AT-NaLanT's pipeline architecture.

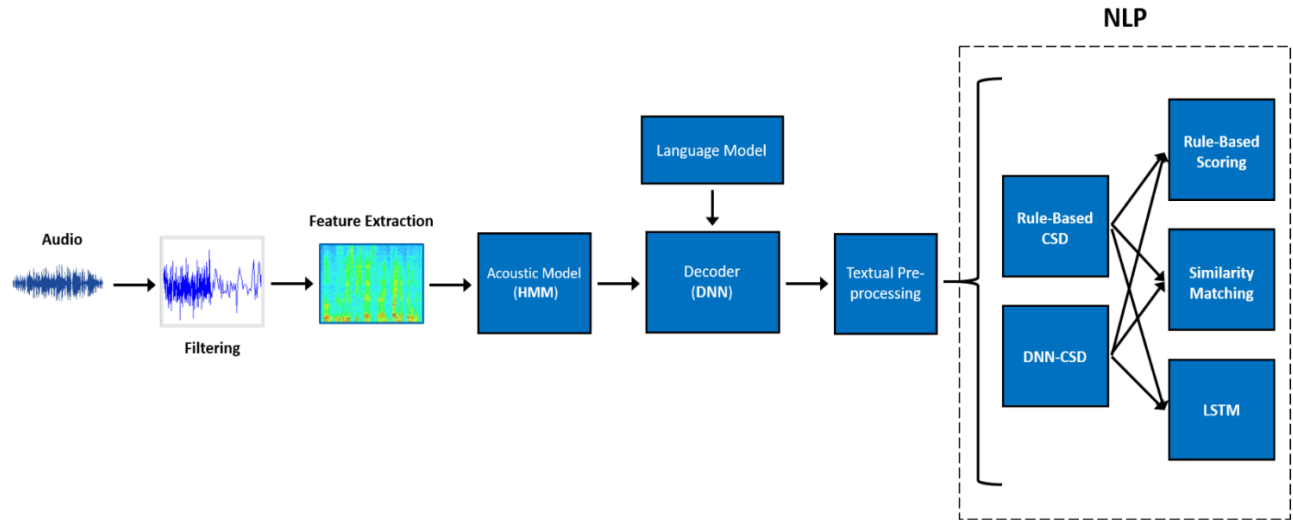


Figure 3. AT-NaLanT Automatic Speech Recognition and Natural Language Processing Ensemble Intelligent Machine Agent Pipeline. Credit: NASA

Because ASR is the NLP's real-time task for computational transcription of spoken language, it was necessary during Phase I development of AT-NaLanT that the initial focus be the NLP IMA. The concerns surrounding the development of an NLP used in the NAS are Call Sign Detection (CSD) and context-relevant Named Entity Recognition (NER) extraction. The simultaneous integration of ensemble rule-based-inference algorithms allows for CSD and NER tasking to take place.

AT-NaLanT's Phase I architectural design consists of the ASR (spoken language conversion to computer readable text) and NLP (CSD and NER extraction) frameworks. The ASR portion is based on the Hidden Markov Model (HMM)/Deep Neural Network (DNN) Hybrid Model represented by Figure 4 [12][13].

B. Intelligent Party-Line Schema

The operational capabilities that are available from the design of C-NAMS are varied and far-

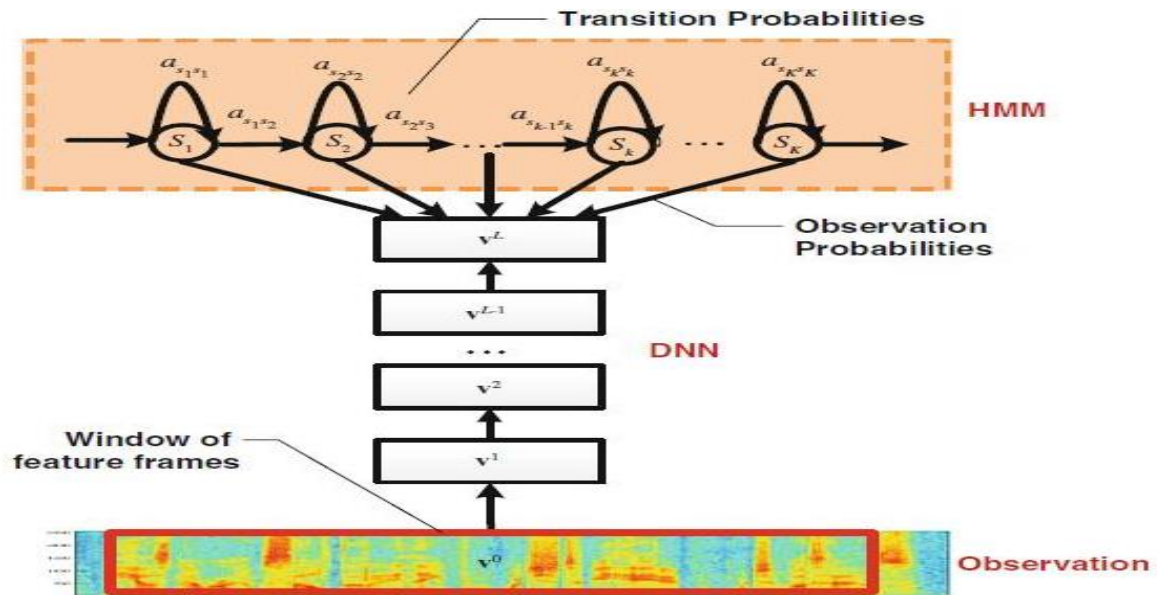


Figure 4. Architecture for the Deep Neural Network-Hidden Markov Model Hybrid System. Credit: NASA

reaching for aviation communication in the NAS, specifically the UAC. One capability that avails itself through C-NAMS' development is the development of an IPL technology. IPL is a technology that allows DAAP the ability to transmit and receive actionable data designated for a specific ownship. IPL significantly minimizes the loss of communications such that DAAP will be able to overcome the Four-V's of big data, which is currently unleashed through the implementation on Next Gen N-CA.

Therefore, significant improvements were obtained in the ability of AT-NaLanT to learn non-linear functions when the DNN/HMM hybrid modeling system was applied (see equation 1). The DNN does not provide the conditional likelihood, necessary for HMM, and uses a framewise posterior distribution to turn the probabilistic model of $P(x_t|s_t)$ into a classification problem $P(x_t|s_t)$. This creates a pseudo-likelihood technique that acts as an approximation of the joint probability[11]. In equation 5, the numerator is a DNN classifier, trained with a set of input features as input x_t and target s_t . The denominator $P(s_t)$ is the prior probability of state s_t .

$$\prod_{t=1}^T P(x_t|s_t) \propto \prod_{t=1}^T \frac{P(x_t|s_t)}{p(s_t)} \quad (5)$$

The selection of the DNN/HMM hybrid model was necessary due to the challenges associated with building ASR and NLP algorithms, particularly for aviation audio and textual communications. Issues that presented themselves, within the NAS, are the lack of available annotated data, unique alpha-numeric phrasing and pronunciation, low signal-to-noise ratio, and high articulation variance. High accuracy model performance, under those circumstances, would have meant thousands of hours of annotated data would be necessary, which was not a feasible approach during this phase of development.

Preliminary testing and analysis were conducted to establish a CSD baseline. The NLP was tested at a two-hour interval, on a subset of sample data that consisted of 808 audio annotations containing aircraft call signs. Rule-based CSD followed by Levenshtein similarity matching and rule-based grading yielded a detection accuracy of 78.6%. This shows that with the addition of other ensemble algorithmic components, a higher and consistent accuracy can be achieved.

III. INTELLIGENT PARTY-LINE SCHEMA

The IPL schema is developed to leverage the acquisition of real-time streaming data being formulated into actionable information for immediate use by the DAAP. The IPL is derived from C-NAMS's RTDA and two of its IMAs, Traffic Data Manager (TDM) and the At-NaLanT. The IPL autonomously provides the DAAP with a real-time synchronized visual (TDM), auditory and textual (AT-NaLanT) platform. The IPL technology and its application has the potential to decrease operator workload by providing only relevant information (audio, visual, textual). This is expected to substantially increase the DAAP's ability to perceive and comprehend N-CA available flight data and perform mitigation management. Implementing IPL in the NAS operational environment is predicted to make the Three-Vs of big data manageable by the DAAP.

IV. DISCUSSION AND FUTRE RESEARCH

Work continues to be done in developing the autonomous triggering necessary for silencing all irrelevant data and limiting most maybe-relevant communications. IPL will be essential in preventing unnecessary communications in the DAAP's operational environment. Additionally, C-NAMS RTDA will be used to ingest MAVLink data in support of the T³ Projects Bi-Directional (Machine-To-Human) Communication work [14].

Also, the IMAs that make up the Network System of C-NAMS will be retrofitted for existing IMAs and created with, in the case new IMA developments, with the Self-Supervised Learning (SSL) technique. SSL lessens the need for large amounts of training data and human oversight. The IMA can then, on its own, determine which features it needs to learn a task from, drawing conclusions based on observed connections and correlations.

ACKNOWLEDGEMENT

The authors would like to acknowledge the following members of NASA Langley's Crew Systems and Aviation Operations Branch (CSAOB) and the Autonomous System Integration Branch (AISB) for their managerial support : Randy Bailey (CSAOB), Jennifer L. Kibler (CSAOB), Eric Chancey (CSAOB), and Lisa Le Vie (AISB).

REFERENCES

- [1] Join¹ Staff Washington, D.C. 20318-6000, "Net-Centric Operational Environment Joint Integrating Concept" October 2005
- [2] Big Data London Conference, November 2017
<https://bigdataldn.com/intelligence/big-data-the-3-vs-explained/>
- [3] V. E. Houston, W. J. Manuel, E. Gizzi, B. A. Barrows, "Advancing Aircraft Operations in a Net-Centric Environment with the Incorporation of Increasingly Autonomous Systems and Human Teaming," Proceedings of the 2019 AIAA Aviation Forum, Dallas, TX, USA, June 2019
- [4] V. E. Houston, "An Approach to Autonomous Contingency Management in Urban Air Mobility: The Communication Network Awareness Machine System" Proceedings of the 2020 DASC Virtual Conference, October 2020
- [5] B. Chambers and M. Zaharia, "Spark The Definitive Guide: Big Data Processing Made Simple", O'Reilly Media, 1st ed, pp. 4-8, March 2018
- [6] P. K. Pandey, "Real-Time Stream Processing Kafka Streams", Learning Journal, 1st ed, pp. 29-40, March 2019
- [7] T. White, "Hadoop The Definitive Guide: Storage and Analysis At Internet Scale", O'Reilly Media, 4th ed, pp. 3-15, April 2015
- [8] "Designing a Production-Ready Kappa Architecture for Timely Data Stream Processing", <https://eng.uber.com/kappa-architecture-data-stream-processing/>
- [9] Breiman, L. "Random Forests." Machine Learning 45, pp. 5–32, 2001.
- [10] V.E. Houston, L .R. LeVie, "Autonomous System Technologies for Resilient Airspace Operations.", Proceedings of 2017 AIAA Aviation Forum, Denver, CO, USA, June 2017
- [11] Bishop, C, M., "Pattern Recognition and Machine Learning", February 2006
- [12] D. Yu, L. Deng, "Automatic Speech Recognition A Deep Learning Approach", Springer-Verlag London 2015, 1st ed, pp. 99-134
- [13] U. Kamath, J. Liu, J. Whitaker, "Deep Learning for NLP and Speech Recognition", Springer Nature Switzerland AG 2019, 1st ed, pp. 369-402
- [14] J. B. Holbrook, L. J. Prinzel III, E. T. Chancey, R. J. Shively, M. S. Feary, Q. V. Dao, M. G. Ballin, C. Teubert, "Enabling Urban Air Mobility: HumanAutonomy Teaming Research Challenges and Recommendations", Proceedings of 2020 Virtual Event AIAA Aviation Forum, June 2020