Toward the Development of a Low-Altitude Air Traffic Control Paradigm for Networks of Small, Autonomous Unmanned Aerial Vehicles

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To enable safe and efficient operation of a large number of Unmanned Aerial Vehicles (UAVs) as envisioned in future commercial operations, a novel networked-based air traffic control paradigm is needed to provide for autonomous route optimization and cooperation to enable deconfliction. This system would need to ensure deconfliction from nearby manned and unmanned operations and would need the capability to respond to unexpected close-proximity aircraft, known as interlopers. This network-based control paradigm will require that operators be able to oversee a network of cooperative and autonomous UAVs capable of maneuvering at low altitudes. Such a network would need new algorithms and increased autonomy to best support cooperative deconfliction and high level supervisory control, and one that also allows operators the ability to both understand local and global behavior of a network of UAVs. To this end, we propose a paradigm-shifting multi-layer distributed air traffic control concept focused on low altitude, high density UAV operations. This new architecture would include a group of analysts that perform a global analysis of the UAV network at a strategic level and more tactical, local controllers manipulating the UAV network, who are advised by the analysts. The proposed operational support system would include methods for the automatic identification of issues within the network, as well as a method for the automatic distribution of effective tasks to the most suitable personnel. This architecture would be a combination of current air traffic control techniques as well as those troubleshooting techniques found in other domains like network and cloud computing management.

Nomenclature

$\mathbf{E}$	=	error matrix
M_n	=	n^{th} metric
$\mathbf{T}$	=	task
$\mathbf{P_n}$	=	n^{th} Air Traffic Operative (ATO)

I. Introduction

The interest in using Unmanned Aerial Vehicles (UAVs) in commercial settings is rapidly increasing. It has been estimated that 15,000 unmanned units will be employed by 2020 according to the Federal Aviation Administration (FAA)[1]. A key concern raised by this increase is how these potential large networks of commercial drones can be monitored and controlled. Conventional Air Traffic Management (ATM) systems have been proven to be inefficient to the extent that the addition of large dense networks of UAVs cannot be supported[2]. This inadequacy is not just from the chaotic nature of existing ATM infrastructure but also from the different human-centred requirements and roles for controlling these large networks[2].

This paper presents a new proposed ATM paradigm for the supervisory analysis and control of such large UAV networks. The proposed ATM system incorporates novel human dynamics developed on the principles of cognitive psychology and novel operational support systems that uses computational techniques such as machine learning to aid personnel in a human-computer collaboration paradigm.

This effort examines the requirements for a successful ATM system given the commercial UAV paradigm, as illustrated in Fig. 1. The first key requirement is that the system needs to allow personnel to ensure safety in this complex network in both predictive and reactive scenarios. Second, the system must prioritize scalability in order to

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ensure that it can support the future of commercial operations. Finally the system must ensure that the interface between the personnel and this complex system prioritizes a ratio of intuitiveness and flexibility to ensure that the personnel can operate in an optimal way.

A key assumption is that, at least in initial phases of operation, this low altitude, high-density UAV management system would operate in parallel to the manned air traffic control system and that there would be coordination between the two, particularly in airport traffic areas.

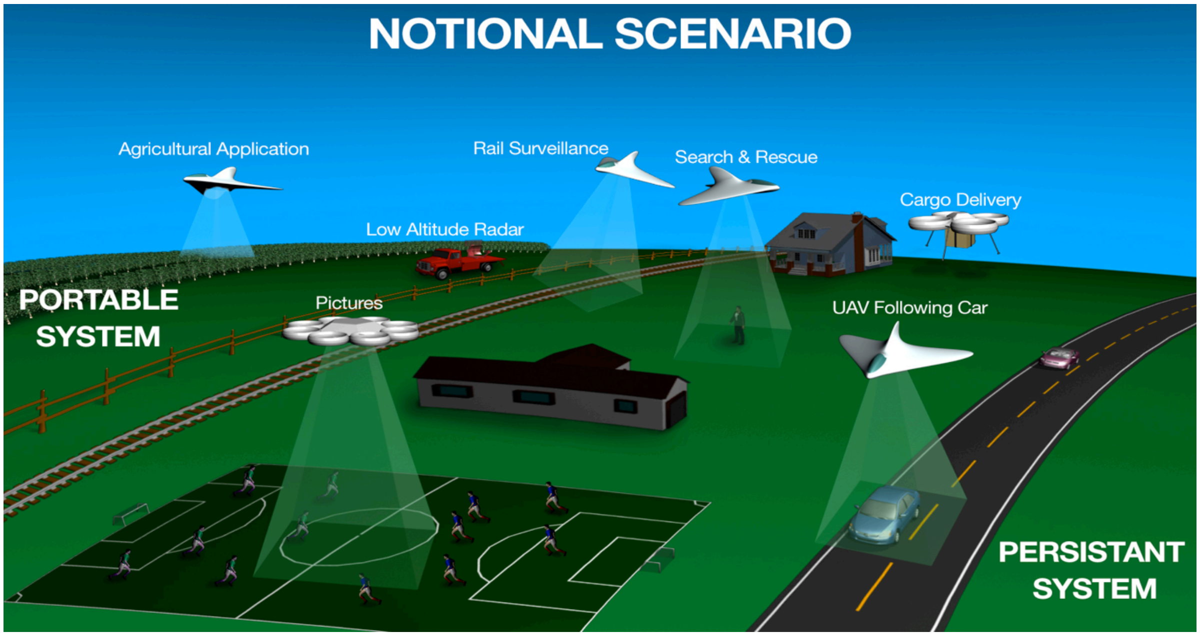

Figure 1. National scenario of UAV operations, courtesy of NASA.

II. System Overview

The proposed Air Traffic Management (ATM) paradigm has three core components supported by a range of external systems and bodies as seen in Fig. 2. This structure has been designed to support human team dynamics, data processing and human computer interaction in order to aid in the identification and resolution of issues within the UAV network. This section will introduce the systems that support the proposed ATM paradigm while the actual paradigm will be detailed in a following section.

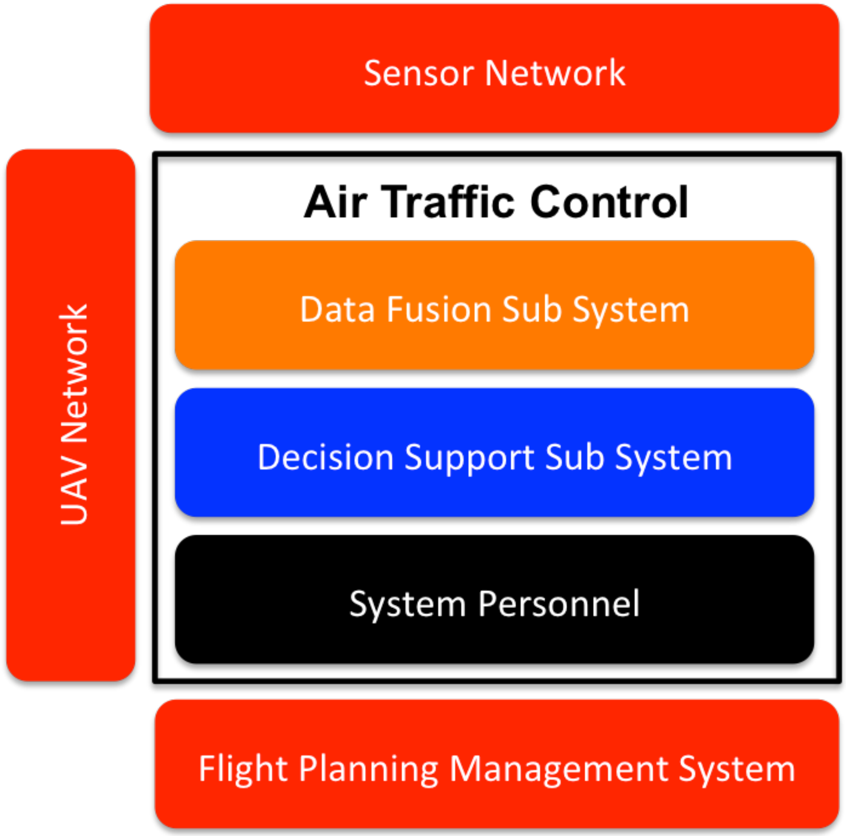

Figure 2. System overview.

A. Sensor Network

The futuristic ATM system would be supported by a network of sensors that provide a range of information regarding the network of UAVs. This section presents the processed data types that are expected to be available to the ATM system and examples of sensors that this next generation system could utilize to meet these data groups.

- Geographical Positions of UAVs

  This data is key in visualizing the location of all UAVs in the network to help the ATM detect a range of violations and issues within the network such as rogue operations and unexpected network densities. This data also aids in automatic identification of issues within the network. Possible stationary sensors to achieve this include:
  - Distributed Positional Radar[3]
  - Distributed Ultra Wide Band Positioning[4]
- Operating Environment Weather Data

  This data is key in identifying weather-related issues that could be catastrophic to the system. Possible sensors to achieve this include:
  - Distributed Weather Radar[5]
  - Distributed Lightening Detection[6]
  - Distributed Low Level Windshear Sensors[7]
- Satellite Imaging Data

  This data is extremely useful for the validation of issues that have been detected from other sensor data as well as an invaluable tool for emergency scenarios. This data will come from geostationary imaging satellites[8].

B. UAV Network

Data directly from the UAV is also necessary for the ATM to perform optimally, which would include:

- Absolute and Relative Positions of UAVs

In addition to the need for absolute positional information as described above, it is also important that such a network would also support the communication of relative positions of both manned and unmanned aircraft in the network. Sensors to achieve this extra data includes:

- Onboard Global Positioning Systems
- Onboard Automatic Dependent Surveillance Broadcast
- Inertial Navigation Systems

- Local Position Prediction

  This data allows for potential issues that occur when drones fly too close to each other which has the potential to cause crashes and could also be an indicator that the airspace is inadequate for the current operations. Sensors that aid in detecting these violations include:
  - Onboard Vision Systems[9]
  - Onboard LiDAR Sensors[10]
  - Onboard Thermal Sensors[10]
  - Onboard Acoustic Sensors[10]
  - Onboard Millimeter Wave Radar[10]
- UAV Health Status

  This data will aid in the identification and prediction of potential incidents for drones that experience system anomalies. Sensors to gauge the health of an individual UAV include:
  - UAV Onboard Positioning Sensors[11]
  - UAV Navigation and Communication Sensors
  - UAV Power Sensors
  - UAV Control Surfaces Sensors
  - UAV Fuel Level Sensors

C. Flight Planning Management System

This external system is responsible for processing requests by UAV operators for flight plans. A general overview of a potential Flight Plan Management System is seen in Figure 3, which details the flow of operations within that system.

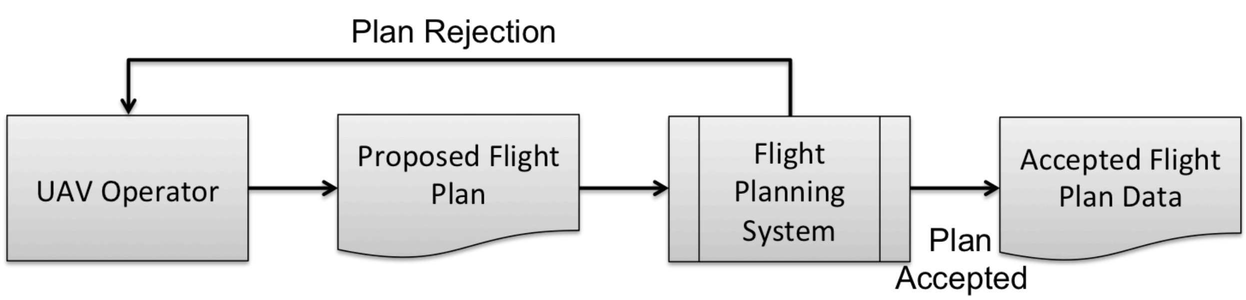

Figure 3. Flight plan management system overview.

The Flight Planning System is responsible for a range of important tasks, including Automatic Path Planning and temporal Scheduling while ensuring that there are no conflicts within the proposed flight plan for either manned or unmanned aircraft. Such a system requires the following data:

- UAV Operating Area

  This data allows for the effective visualization of network flow as well as provide insight to potential future incidents within the network. This set will contain the destination, origin, flight path, and UAVs' in-flight activities.
- UAV Operator Information

  This allows for effective resolution of issues concerning UAVs within the network by allowing the ATM to identify the operator of the UAV and, therefore, allow effective coordination between the operator and the relevant ATM personnel.
- UAV Specifications

  This data allows for effective calculation of UAV dynamics to aid in the prediction of issues within the network. The onboard payload will be provided in this data set, as well as any constraints about the payload such as time of delivery

III. Proposed Air Traffic Management Architecture

The proposed Air Traffic Management (ATM) architecture for low altitude, high density UAV operations proposes two core concepts that improve upon conventional ATM systems. The first is a novel personnel structure that separates out the analysis and effective tasks from the network into two groups, which are the Air Traffic Analysts (ATAs) who provide strategic analysis and the Air Traffic Operatives (ATO) who manipulate the network to ensure safety. The second is the use of computational techniques to automatically provide operational support to the personnel both in terms of analysis through the Automatic Issue Identification (AII) system and collaboration through the Automatic Task Distribution (ATD) System.

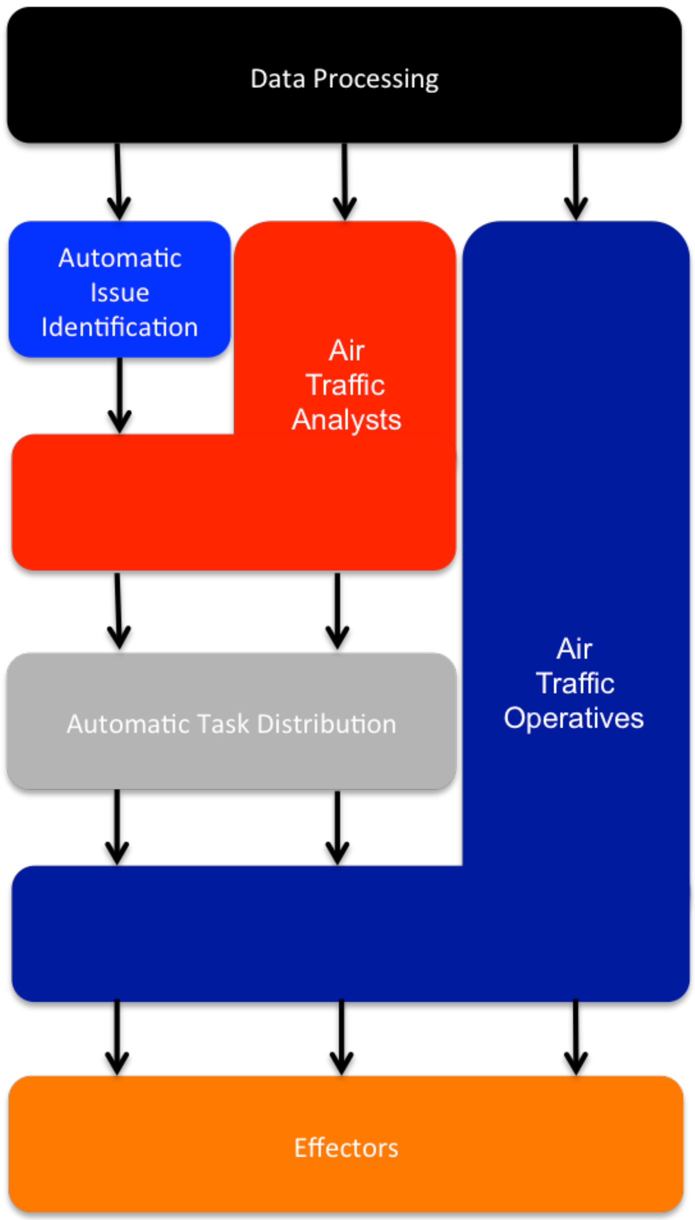

Figure 4. Structure of proposed air traffic management system.

Figure 4 shows the flow of the proposed Air Traffic Management system. As can be seen the first layer is data processing, this layer will take raw data from the external systems and process it into a manageable form. This processed data is then used by the parts of the system whose task is to perform some level of analysis of the UAV

Network. These parts are the Automatic Issue Identification (AII) system, the Air Traffic Analysis (ATA) personnel and the Air Traffic Operative (ATO) Personnel.

The Automatic Issue Identification (AII) system applies computational techniques to the data to automatically flag issues within the network. The Air Traffic Analyst personnel use both the processed data and any issues generated by the AII system to determine if anything in the UAV network needs to adjust to ensure safety. The processed data is used by the Air Traffic Operative personnel to determine the best way to manipulate the network to ensure safety or to resolve issues to mitigate the impact across the network. When a task is identified during the analysis performed by the ATA personnel, this is then distributed to the ATO personnel through the ATD system that identifies the most appropriate ATO to affect the network based on a range of factors.

The final phase of the system is for an ATO to affect the network shown by the effector layer in Figure 4. This layer signifies that the ATO manipulates the system in some way, some possible examples of this include coordinating with emergency services to manage a crashed UAV or perhaps a simple change of flight paths to reduce the risk of a crash. It should be noted, however, that the effective tasks in this paradigm are dependent on the way in which all aspects of the global system develop, therefore a more complete taxonomy of tasks will evolve as developments happen.

The following sections detail all of the elements of the proposed ATM paradigm, detailing their goals, structure and why they are needed by the system to meet the requirements of a viable solution to manage the next generation of commercial UAV operations.

A. Data Fusion and Processing

In Figure 4, the system consists of an initial data processing layer to process the data into a form suitable for both the human and computational aspects of the system, which could include machine learning to reason about the data and determine higher-level descriptions that are more intuitive for the human personnel. The data processing layer is also critical for the algorithms that need to be developed to identify issues, as seen in the Automatic Issue Identification (AII) layer, and distribute and schedule tasks, as seen in the Automatic Task Distribution (ATD) layer.

B. Automatic Issue Identification System

Figure 5 shows the flow of the system from raw data to task generation, specifically where the Automatic Issue Identification (AII) system integrates with the Air Traffic Analysts (ATA).

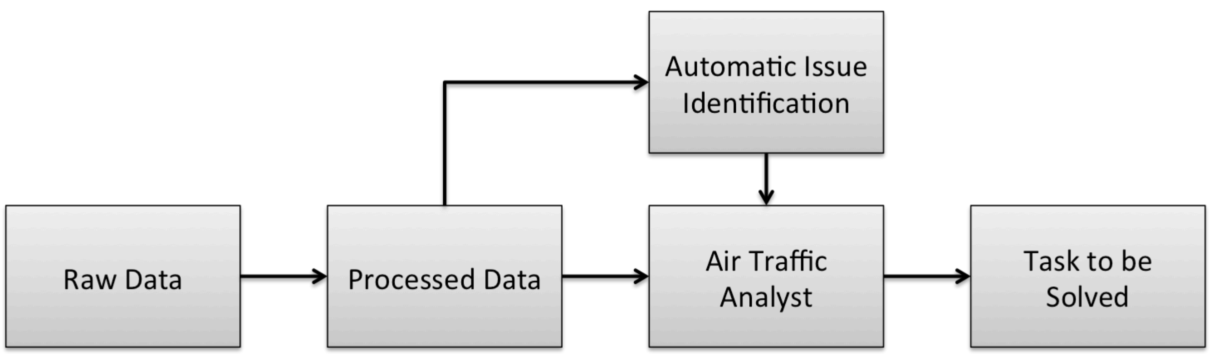

Figure 5. Task generation flow.

The system proposed would be a cluster of algorithms that detect and classify anomalies within the network and returns issues. The two core techniques include:

- **Anomaly Detection** – Anomaly detection will be used to detect differences between actual progresses of UAVs at any given time in comparison to the progress filed as part of the flight plan. This will allow for the identification of rogue operations as well as if UAVs are not performing as expected. Some examples of anomaly detection techniques are described[12,13,14].
- **Pattern Matching** – Pattern matching could be used to identify any anomalies in the network by matching the generated anomaly to a database of patterns. This matching will aid in initially providing a greater depth of information to an ATA that will allow for a much more effective validation and resolution of an identified issue[15].

C. Air Traffic Analysts

The proposed core role of Air Traffic Analysts is to perform a global analysis of the network in order to identify issues that could be detrimental. A secondary function of a given ATA is to validate issues generated by the AII system to ensure that the automatically identified issues are indeed real. In order to perform these analyses and validations, an intuitive interaction and visualization paradigm is needed that allows ATA personnel to monitor data and make decisions within a minutes-to-days time scale. The ATAs can be seen as strategic planners who attempt to optimize the entire network, while the Air Traffic Operatives are tactical planners working on a local level.

After a given issue within the network has been identified and validated, an ATA, with the assistance of an automated decision support system, formalizes the different tasks that are required to solve this issue. In order to formalize a given issue, an ATA will generate tasks that contain all relevant information about a given event in the system as well as a priority level for the tasks. This priority is ensures that the task gets resolved within a task specific duration.

D. Air Traffic Operatives

The ATD system assigns tasks to the Air Traffic Operatives. This group is concerned with resolving the tasks by affecting the network and coordinating with both manned and unmanned aircraft. If there are a high volume of tasks that are being generated an on-call paradigm is proposed to the extent that if personnel are becoming overloaded on-call ATO personnel are notified and are able to relieve the pressure by resolving tasks from any location.

E. Automatic Task Distribution

Once a task has been generated by an ATA, it is processed by the Automated Task Distribution (ATD) system and matched to the most appropriate ATO that is currently available. The proposed ATD algorithm takes data from a range of sources:

- Data from current task
- Training data of ATO personnel
- Past performance of ATO personnel
- Data regarding each active ATO's shift including performance measures and workload levels

This data is then fed through a novel algorithm shown in Figure 6 that computes an error matrix **E** between a metric matrix **M** from a given task **T** and all active ATO personnel **P**. This error matrix is then sorted using MinSort, an algorithm that sorts a given error matrix in terms of row wise values. The algorithm returns a matrix **S** of personnel that are ranked based on their suitability to that given task.

$\mathbf{P} = \{\mathbf{P_1, P_2, \ldots, P_n}\} : \mathbf{P_n} = \{\mathbf{M_1, M_2, \ldots, M_n}\}$
$\mathbf{T} = \{\mathbf{M_1, M_2, \ldots, M_n}\} : |\mathbf{T}| = |\mathbf{P_n}|$

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for i → 1 to |P|
    for j → 1 to |T|
        E_I,J = Error(P_I,J, T_J)
    end
end

S = MinSort(E)
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Figure 6: High-level automatic task distribution algorithm.

The personnel matrix is later filtered based on the ATO current and projected workload, as well as the availability and task load of the ATO personnel. This allows for the selection of the ATO that is currently in the best position to solve this task within the required time frame.

F. Conclusions

The goal of this research was to propose an Air Traffic Management paradigm that can ensure the safety and efficiency of future UAV operations. The presented research proposes a supervisory paradigm that introduces two core groups of personnel that work on a strategic as well as tactical level.

The proposed personnel structure that consists of a group of personnel to perform a global analysis of the UAV network (ATA) and a group of personnel concerned with effecting the UAV network (ATO) based on the analysis performed by the ATAs. It is believed that this proposed personnel structure would allow for the seamless supervision of the network through optimizing personnel workload, while ensuring an environment that allows for the accurate identification and prediction of issues within the network to ensure safety.

The proposed operational support systems include methods for the automatic identification of issues within the network, as well as a method for the automatic distribution of effective tasks to the most suitable personnel. This proposed system is heavily dependent on the development of the entire commercial UAV paradigm ad therefore it is important that this system goes through multiple iterations in parallel with the development of the development of other aspects of the system.

This proposed Air Traffic Management architecture lays the groundwork for a paradigm-shifting multi-layer distributed air traffic control concept focused on low altitude, high-density UAV operations. Simulations need to be conducted both in terms of network viability as well as human-computer teaming to determine the specific research gaps and areas for improvement. This architecture would be a combination of current air traffic control techniques as well as those troubleshooting techniques found in other domains like network and cloud computing management. Such a system would require substantial new computational approaches as well as advanced forms of supervisory control and human-computer collaboration.

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