Dynamic Network based Learning Systems for Sensor Information Fusion

Dinesh Verma*[a], Simon Julier[b]
[a]IBM TJ Watson Research Center, 1110 Kitchawan Road, Yorktown Heights, NY 10598, USA
[b]Dept. of Computer Science, University College London, London WC1E 6BT, UK

ABSTRACT

In order to get the modularity and reconfigurability for sensor information fusion services in modern battle-spaces, dynamic service composition and dynamic topology determination is needed. In the current state-of-the-art, such information fusion services are composed manually and in a programmatic manner. In this paper, we consider an approach towards more automation by assuming that the topology of a solution is provided, and automatically choosing the different types and kinds of algorithms which can be used at each step. This includes the use of contextual information and techniques such as multi-arm bandits for investing the exploration and exploitation tradeoff.

Keywords: coalition operations, distributed learning, machine learning, Model merging

1. INTRODUCTION

Sensor information fusion is a key problem in almost any military operation. Many of these difficulties are compounded in coalition operations, where sensors and fusion services are owned by different partners with limited interoperation and information exchanges between them. A significant amount of work exists for both low level information fusion (which uses techniques such as signal processing, filtering, weighted averaging and object state estimation) as well as high level information fusion (which employs techniques for situational awareness, threat assessment and process improvement, policy refinement etc.) High level information fusion [1] uses techniques which can span semantic technologies, rule-engines, policies, and machine learning algorithms. Information fusion techniques at both the high level and low level can be combined in various manners for specific domains, e.g. robotics [2], wireless sensor networks [3] or intelligent transportation systems [4]. The fusion of information of many different sensor data can be done using a variety of algorithmic approaches, which range from weighted averaging methods, Kalman filtering [5], Bayes estimation [6] to algorithms deploying advanced machine learning and cognitive computing capabilities such as Dempster-Shafer reasoning[7], fuzzy logic[8] and neural networks[9]. In this paper, we look at the challenges for information fusion which arise in machine learning algorithms in coalition contexts, and discuss approaches to address those challenges.

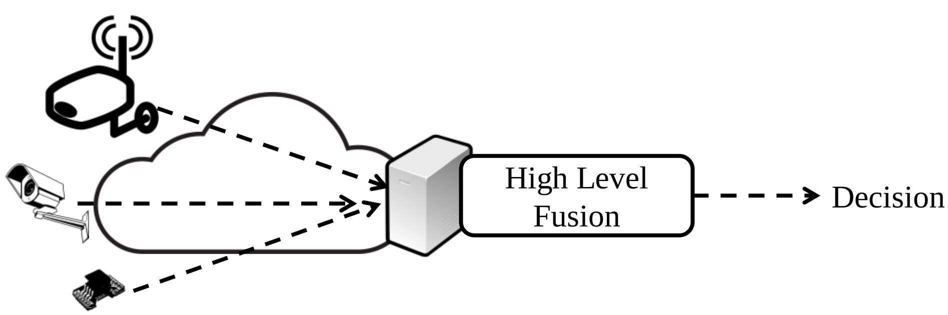

Figure 1. Information Fusion Environment assumed for each coalition partner

The paper assumes a scenario which consists of several coalition partners who are working together to perform a task which requires fusion of sensor generated information. We assume that each of the coalition partners performs high level information fusion using some machine learning algorithm using the setup shown in Figure 1 in which a high level fusion service is fed by data input from many different sensors. The service makes high level decisions, such as assessing the threat level, recognizing objects, identifying a person of interest etc. The output of that is a decision -- such as the quantitative level of threat in an environment, or the type of object a camera has captured, or whether a selected person of interest has been identified.

Within each of the coalition members, we assume that the high level information fusion process follows a cognitive or machine learning approach as shown in Figure 2. We define this approach as consisting of two stages, a model learning stage and an inference stage. During the machine learning stage, through a stage of learning/training to build a model for machine learning. Such models can represent various techniques, but for the purposes of this paper can be thought of as any model that can be represented using a standard such as PMML [10].

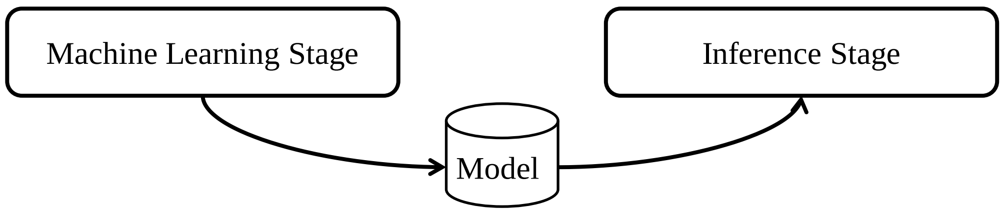

Figure 2. Learning and Inference stage for each coalition partner

During the machine learning stage, the model can be created using a variety of techniques. One model for a machine learning stage will be the case where a human provides the model, e.g. if the model consists of a set of rules or decision trees, a human defines those rules or decision trees. However, the most likely scenario we want to consider is where the model is the result of a machine learning algorithm which has been performed on a set of training data. As an example, if a machine learning program is shown many different images of vehicles, it could train a neural network which is capable of inferring the type of vehicle from a new image. Such models can either be built in a one-shot manner, i.e. they are created by provided a specific training set, either offline or online. Offline mode refers to tasks done when the learning system is not using data generated by the set of sensors connected to it. Online mode refers to tasks done when the learning system is using the data that is collected by the sensors connected to it. In online mode, models can be created and trained during some special base-line periods, or be updated at some specific times. Once the model is trained, the system uses the information from the sensor input feed to check against the model and perform its task.

In a coalition environment, each member of the coalition may learn its own model and using it for its own inference. However, there may be many cases where the models may need to be shared among the different partners. This model sharing leads to interesting and unique problems for coalitions which need to be addressed. In the next section, we discuss some of the common scenarios which may arise in a coalition environment. The scenarios are followed by the main challenges in using machine learning techniques in coalition settings, with the focus being on the challenges involved in sharing the knowledge gained in different partners. This is followed by a abstract representation of the problem in coalition settings that we are trying to solve, a representation which will apply to all of the scenarios and the abstract problem definition. We survey the possible approaches to address the problem, and go into details of one of the approaches we believe have a good potential for solving this problem -- namely network based machine learning.

2. COALITION SENSOR INFORMATION FUSION LEARNING SCENARIOS

There are many scenarios in coalition operations where each of the partners is using the setup shown in Figures 1and 2, or some variation thereof. In this section we describe some of those scenarios and the research challenges that are posed by each of those scenarios.

2.1 Joint Surveillance Scenario

In the first scenario, we consider the case of coalition operations where multiple partners are conducting surveillance information in a region that they are required to stabilize between two adversarial parties. Figure 3 illustrates the scenario. After a period of active aggression, the two adversarial nations have reluctantly agreed to a cease-fire line. The coalition forces are positioned as observers to maintain peace along the cease-fire line. Surveillance equipment along the borders monitor the forces of both adversaries, and could trigger the coalition members in case they need to mobilize additional forces and attempt to prevent a conflagration. The adversaries, or selected elements among the adversarial nations, are always looking for clandestine attempts to infiltrate and attack the other side. Advance warning of such attacks is the goal of the coalition surveillance, and on identifying any such movements, the coalition members inform the two parties to prevent such infiltration. Base camps of coalition members, U.S. and UK house the analysts who look at the surveillance data and make a decision.

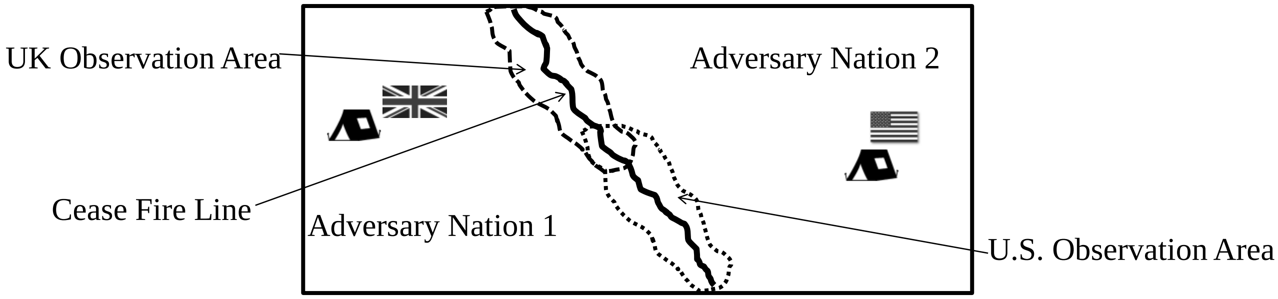

Figure 3. Joint Surveillance Scenario

Since the elements trying to cross the border are likely to be aware of the surveillance equipment in the field, they will use a variety of camouflaging techniques to hide their movement. As a result, the two forces need to continuously learn and upgrade their model for identifying the common ways that the adversaries try to hide their equipment and people. Due to differences in the terrain, the UK is likely to get much more data and footage of insurgents operating from one adversary nation, while the US is likely to get more data and footage of those operating from the other adversary nation. In order to make each other's surveillance more effective, both U.S. and UK want to share their knowledge with each other. However, national policies prevent the sharing of raw videos and footage of the insurgents, some of which has been provided to each country under special arrangements, and each country is worried about possible leakage or misuse of the raw video by the other country. The analysts at both the U.S. and UK camps have reached a conclusion that if they share the models that they obtained by training their learning algorithms, that will be allowed under national policies. Therefore, they want the ability to share the model they have both learnt independently.

2.2 Assistive Fleet Scenario

Autonomous devices such as drones, mules and robots have started to be used by soldiers, and in the future, such devices are going to proliferate and many such devices will be supporting a platoon. Such an assistive fleet may consist of drones that go out and survey the landscape from the skies and several mules that will carry heavy backpack and supplies. Additional drones and mules may carry ISR equipment, which may be scanning the environment continuously for acoustic patterns, radioactive elements, or toxic chemicals.

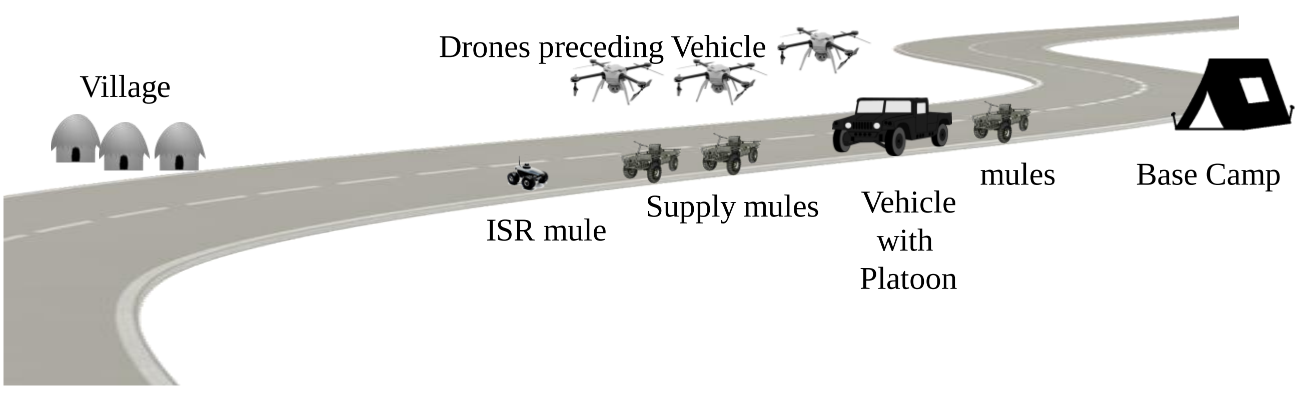

Figure 4. Assistive Fleet Scenario

As a platoon drives from a base camp for a task, e.g. deliver humanitarian assistance to a village, the vehicle will be accompanied by drones and mules that will travel along with the vehicle, as illusrated in Figure 4. As the drones collect footage along the path from the skies, the mules will collect the footage from the ground. Future drones and mules will have enough processing power to perform both the machine learning as well as the inference tasks required for high level information fusion.

In this situation, the models that each done and mule learn about any potential threats along the path would tend to be different since they would each be training their models based on the different images they obtain. In an ideal case, each of the drones and mules would share the video and other surveillance data with each other. However, since the devices are operating in a dynamic tactical environment, the communication bandwidth available to them may be fairly limited, and such sharing among all of the members of the fleet may not be possible.

A logical solution in those cases will be for the devices to use their individual collected information to train models individually, and then to go through a model merging process.

2.3 Dynamic CoI Scenario

In coalition operations, communities of interests (CoI) which are short-lived teams need to be formed for various missions. Such a dynamic CoI may include multiple coalition members, and requires assets belonging to different coalition members to be shared among the CoI members.

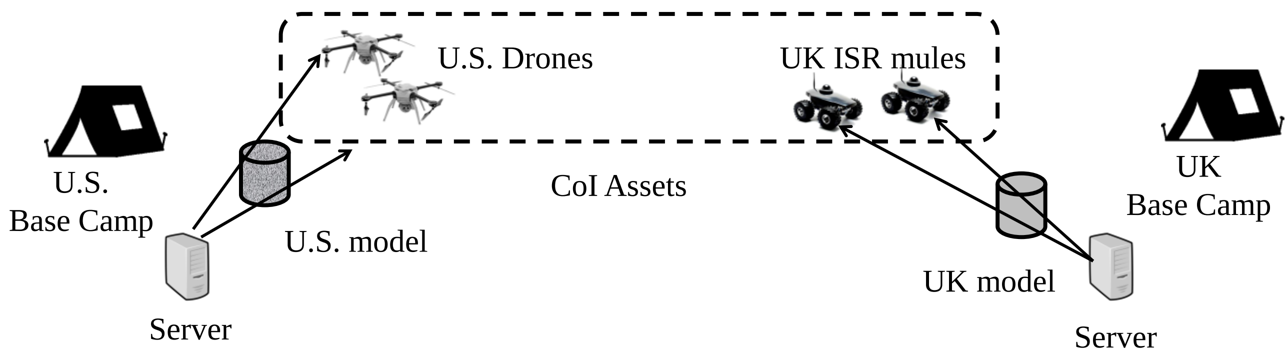

Figure 5. Dynamic CoI Scenario

Let us consider the scenario where some surveillance drones belonging to the U.S. are shared in a dynamic CoI which involves some UK personnel. The dynamic CoI is being led by a UK commander for the mission, and the task of the CoI is to detect for hidden IEDs along a path. In order to do that task, the UK commander will use the U.S. drones as well as a set of ground vehicles that the UK operates.

Both the U.S and UK vehicles have been tasked with the charge of performing the inference stage of the high level information fusion to detect for IEDs. In order to make them work efficiently, a server at the base camp of each country has trained their devices with the inference model. When the devices are brought together for the mission, the commander would like all the models to be shared across all devices during a pre-mission phase so that each of the CoI vehicle benefits from the models available at each of the assets. One the mission is operational, the different assets only perform the inference task on the merged model.

In each of the above scenario, we see that there is a need for merging models that are learnt independently by different elements in the network. The challenge of merging models and leveraging the power available from all elements in the network is the problem of network based learning that we address in this paper.

3. NETWORK BASED LEARNING PROBLEM STATEMENT

In this section, we provide an abstract formulation for the network based learning problem and discuss the possible approaches for solving that problem. Figure 6 shows and abstract representation of the problem, as identified by the motivating scenarios described in the previous section.

We define the problem for Network based Learning as a fusion task to be performed among different models that are learnt individually by two or more learning nodes. The fusion node takes each of the individual models, and produces a net output which is the result of the aggregation of each of these models. The actual fusion process would depend on the nature of the model, and some models are more amenable to fusion than other models.

To enable efficient fusion, a coordination node may also need to give some information to the learning nodes so that they are able to coordinate the models that they are learning. This information is the model control information that is shown as flowing from the coordination node to the learning node. This model control information may provide the different learning nodes with information that they need to provide model output that the coordination node can easily fuse together.

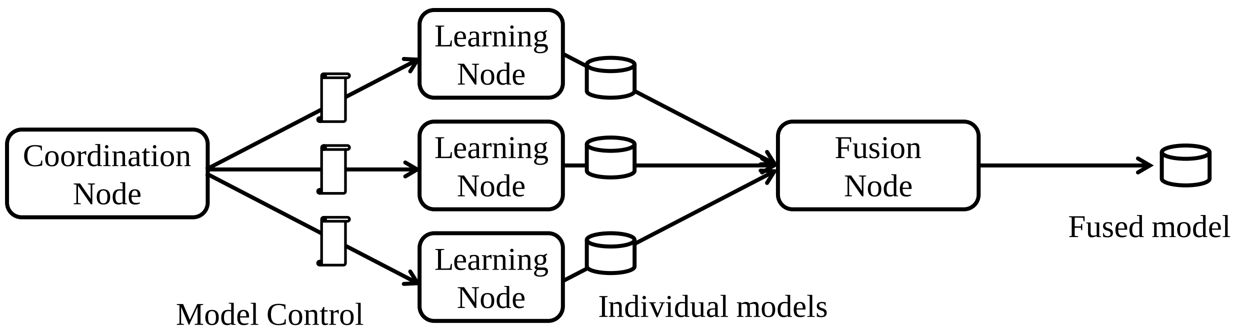

Figure 6. Network based Learning Problem Formulation

In the Joint Surveillance scenario, the model control information may consist of different coalition partners agreeing to create models using the same cognitive or machine learning approach, e.g. they would each use decision tables or each would use a clustering algorithm to create their models. The coordination node function is obtained manually by coordination among different coalition members. The individual models that are then created can then be combined together by independent and separate fusion nodes in both of the two coalition partners.

In the assistive fleet scenario, the coordination node and fusion node may be part of the computing equipment that is carried in the vehicle with the platoon, and the learning nodes are the drones and various mules. Model control can be implemented through a computer communication protocol between different drones, mules and other elements providing cognitive assistance to the platoon. This communication protocol can provide a significant increased level of coordination among the assets, than was possible in the joint surveillance scenario, which has to follow a manual process for the coordination. The fusion can also be done in an automated and frequent basis.

In the dynamic CoI scenario, the coordination task cannot be performed before the learning phase since the assets have been pre-trained before they became part of the CoI. However, a coordination phase may have the CoI commander determining the subset of different models that can be transformed into each other, and then result in a format that can be fused together. This scenario illustrates that the relative temporal positions of coordination and learning are not fixed. In some scenarios, coordination can be done before actual learning happens, while in other scenario, the coordination can only happen after the learning has happened. The fusion of models without a prior coordination requires more complexity, require filtering and transformation of the models that have been learnt by the different systems.

Although each of the scenario requires a different way for coordinating the learning nodes, and different types of learning technologies may be better suited for the specific needs of different scenarios, the algorithms that we need to developed for the tasks can be classified as belonging to a few general classes. In the next section, we take a look at the types of algorithms that are needed.

4. ALGORITHMS FOR NETWORK BASED LEARNING

In order to be able to attain the task outlined above, three types of algorithms are needed. These algorithms include

- *Model Fusion Algorithms*: When different models are produced by different learning nodes, the different models need to be fused together into a single model. Fusion assumes that all the models being fused together are of the same type, e.g. each of the learning nodes is producing a decision tree, a set of policy rules, or a neural network. Depending on the type of model being used, fusion could be a simple process, or a fairly complex one.

- *Model Transformation Algorithms*: Sometimes two learning nodes will produce models that are not exactly identical. In those cases, the models need to be transformed into a common model so that fusion can proceed. The transformation algorithm will depend on the selection of the original model and the common model.
- *Coordination Algorithms*: If there is a coordination step that can be performed before learning nodes commence their model, the coordination can lead to different nodes producing models that may be easier to fuse and transform after they are learnt. Coordination algorithms consist of approaches which can be used to influence the type of model that each of the learning node learns.

Model fusion techniques for some types of models, such as decision trees have been studied fairly extensively, e.g. in the area of decision trees, several algorithms for combining decision trees in a general manner exist[11]. In these domains, it is also argued why model fusion is a very distinct problem compared to ensemble learning, where many models can be used for inferences in parallel[11], an approach which is more expensive in general. On the other hand, for some types of models, e.g. neural networks, there is substantially less investigation. In some specific domains, e.g. for optical character recognition, Dempster–Shafer based evidential reasoning can be used to combine neural networks [12]. However, since neural networks produce weights that may not necessarily have a physical meaning in the system, a general method for combining different models together for neural networks is difficult to formulate.

The coordination algorithms can help in reducing this difficult problem into a much more manageable system. Instead of trying to merge different algorithms and models which may or may not be related, we can use a coordination mechanism which can result in an easier fusion process. In the next section we describe such a proposed coordination mechanism.

5. TOPOLOGY BASED COORDINATION ALGORITHM

In general, the network based learning approach can assume that different devices in the environment run many different types of services, which can include model inference services, model fusion services, model transformation services, model coordination services, and model learning services. In any specific scenario, these services from different nodes are combined together in a scenario specific manner.

Looking specifically at the inference task, there are two approaches to view the inference activity. One approach is to view the entire inference task as a single service based on a single model. As an example, one can assume that the model used for inference is a neural network, train the neural network during the machine learning stage, and reuse the neural network during the machine learning stage to perform the eventual task of information fusion. Instead of a neural network, one could use another approach, e.g. learn a decision tree, or use a set of classification and clustering algorithms, a ontology etc. depending on the specific nature of the inference task. This would represent the black-box approach for machine learning, where we assume that the data used for training can be used to train a model, but the internal details of the model are hard to understand or represent a-priori. As a result, model fusion between these systems could be very challenging, as discussed earlier.

A contrasting approach is that of using a white-box approach, in which the software or algorithm for the inference task is provided. This would have a human write the decision rules, tables, ontologies, or weights in the neural network, because the human understood how the inference process ought to work. For systems where the relationship between the inputs to the inference service and the output is well understood, the white box approach is suitable. However, it suffers from the problem that the assumed problem may not reflect the actual trends in the data -- since getting a nice clean model is an exception and not the norm in most real-life scenarios. The white box approach defines a set of services and the exact relationship between them, leading to a fixed and well-defined system. Such a system can lead to easy fusion of models. However, this system is rigid and inflexible, not adaptive to the specifics of data obtained during the learning stage.

We proposed an intermediate approach, in which the inference task is viewed as a graph of several inference services, each of them being generated using a given type of model. As an example, let us consider the scenario where the inference service being performed is that by a drone checking if it is under attack. The drone is equipped with acoustics sensors, cameras, processors and network connectivity. The drone may be using a series of inference services, with an illustrate chain sequence described in Figure 7.

Once the structure of the services is known, then the coordination layer can have each of inference services be composed using one of the models that is easier to fuse together, asking each individual learning scheme to develop the appropriate model parameters. Once the model parameters are determined then, the system can determine the right approach to fuse them together. The determination of the exact topology of services and their inference can be made using contextual information. As a subsequent step, approaches like multi-armed bandits can be used to determine the right models to be used at each of the different stages.

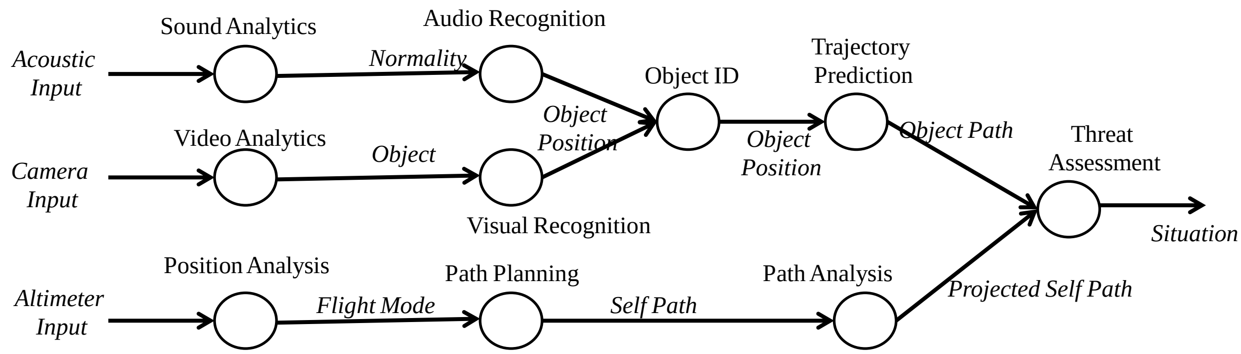

Figure 7. A sample scenario for inference composition

This hybrid approach, which provides a combination of white-box techniques and black-box techniques can then be used to provide an effective approach for model fusion, which incorporates insights from both human experience and the learnt models.

6. CONCLUSIONS AND FUTURE WORK

In this paper, we have outlined an approach for combining models and insights for some common scenarios that are encountered in coalition settings. The approach appears promising in that it addresses may of the key challenges and provides the best combinations of both white box and black box approaches. However, the work we have presented in this paper represents only early ideas, which need to be validated by means of experimentation to ascertain how effective the improvements in model fusion using a network centric approach are.

7. ACKNOWLEDGEMENTS

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