A Bayesian Game Theory Decision Model of Resource Optimization for Emergency Response

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***Abstract*— We describe a system model for determining decision making strategies based upon the ability to perform data mining and pattern discovery utilizing open source information to prepare for specific events or situations from multiple information sources. Within this paper, we discuss the development of a method for determining actionable information. We have integrated open source information linking to human sentiment and manipulated other user selectable interlinking relative probabilities for events based upon current knowledge. Probabilistic predictions are critical in practice on many decision making applications because optimizing the user experience requires being able to compute the expected utilities of mutually exclusive pieces of content. Hierarchy game theory for decision making is valuable where two or more agents seek their own goals, possibilities of conflicts, competition and cooperation. The quality of the knowledge extracted from the information available is restricted by complexity of the model. Hierarchy game theory framework enables complex modeling of data in probabilistic modeling. However, applicability to big data is complicated by the difficulties of inference in complex probabilistic models, and by computational constraints. We focus on applying probabilistic models to resource distribution for emergency response. Hierarchical game theory models interactions where a situation affects players at multiple levels. Our paper discusses the effect of optimizing the selection of specific areas to help first responders and determine optimal supply route planning. Additionally we discuss two levels of hierarchies for decision making including entry decisions and quantitative Bayes modeling based on incomplete information.**

***Index Terms*—Game theory, Resource Management, Decision Making, Operations Research**

I. INTRODUCTION

Game theory is the study of strategic decision making. It is the study of mathematical models of conflict and cooperation between intelligent rational decision-makers and is often thought of as an interactive decision theory. It has been applied to economics, political science, psychology, logic, biology and other complex issues. Modern game theory began with the idea regarding the existence of mixed-strategy equilibrium in two-person zero-sum games, applied to economics. Later this evolved to provide a theory of expected utility, which allowed mathematicians and economists to treat decision-making with uncertainty. The notion of probabilistic predictions utilizing game theory is critical in practice to many decision making applications because optimizing user experience requires being able to compute the expected utilities of mutually exclusive pieces of data which is critical to geospatial analytics.

Economic factors (e.g. unemployment rates, prices for food, such as bread, or fuel), Political factors (freedoms, type of government), Religious factors (type of religions, religious tensions) combined with trend information such as sentiment analysis on social media, open source data, news, etc. can provide indicators of areas undergoing stress or at risk.

Current situational awareness requires efforts to seek to incorporate not only geospatial features and forces structures, but also the human element, especially in urban settings. An attempt to predict the likelihood of reaction to a future event will be based on correct situation analysis. Efforts to combine the information required for these predictions are time consuming and labor intensive. The availability of open source social media information and implementation of artificial intelligence (AI) methodologies makes this problem tractable. Our GlobalSite system, shown in Fig 1, can also be used as a method for asset management and reduce cost of analyses.

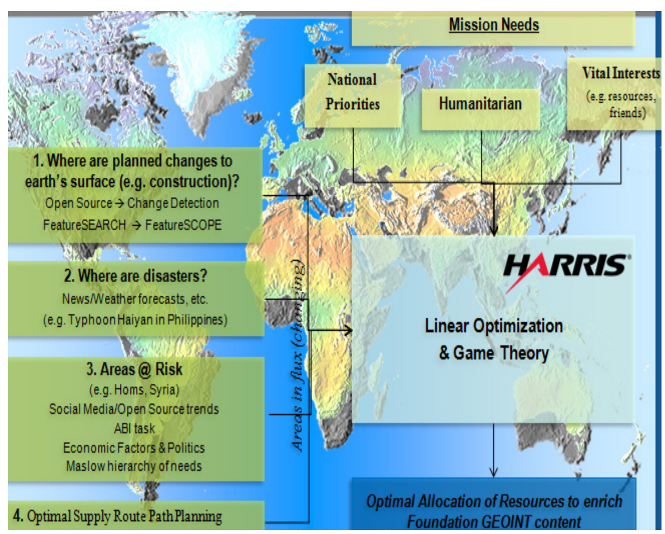

Fig1. Overview

As an example, consider the recent case of Typhoon Haiyan, which devastated portions of the Philippines in early November 2013. Weather data and hurricane/typhoon forecast models could be used to project the path of the storm, and anticipate areas that may be affected. This could lead to enriching Foundation GEOINT content for the Philippines in anticipation of the event (landfall of Typhoon Haiyan), as well as collection of additional data after the event to detect changes, assess damage, and support Disaster Relief/Humanitarian Aid. For instance, change detection may reveal roads have been washed out, presenting logistics problems for the delivery of aid to folks in need.

The Philippines has strategic importance to the U.S. as part of the strategy plans to counterbalance China's rising military influence with strong American allies in the region. The U.S. and the Philippines are in the middle of negotiating an increased American military presence in the country [8].

II. Open Source Data

The internet has forever changed the way people are able to respond to a disaster. Now, a person, business, or organization can create a call to action that generates millions of dollars' worth of donations in money, food, and even volunteer power in a matter of minutes. This can happen via an email, a button on a website, or a YouTube video that goes viral. We have seen this during disastrous events like Hurricane Katrina, the 2010 earthquake in Haiti, or the recent typhoon in the Philippines. The word, "crowdsourcing," is a combination of two words, crowd and outsourcing. Thus crowdsourcing, as it applies to disaster response, is the process of gathering work or funding via the internet to benefit a particular person, organization, or event [9].

What makes crowdsourcing so important is the belief that more heads are better than one. Using the canned food drive as an example, if you were to do the work without the internet, you would have to run around town to various homes and businesses and ask individuals if they would like to participate. This would take up too much time and man power. The internet can be used to send email to friends, who would then pass the word on to their friends. An online donation campaign can be created where one can make a short video as to why people should donate to a cause [9].

The recent typhoon in the Philippines has seen an exciting change in how crowdsourcing can assist in disaster response. Rather than sit and wait for heads of organizations and governments to dictate what is needed on the ground, people are able to assist first responders in the very work of saving lives, both directly and indirectly. Through the use of powerful technology, people are able to track weather patterns that are more accurate than anything you will find on the evening news. Geography buffs are able to use satellite imaging technology to create maps and locate where people are stranded and in desperate need of food and water. There are even examples of people who have been able to locate others who were buried under debris. This kind of response is a much more aggressive response to a disaster [9].

Social media tools like Twitter and Facebook, traditionally looked upon as a game for kids has been useful to relief workers as well. The group Standby Task Force has been able to gather over a million tweets, text messages, and other social media updates to track the extent of the damage in near real time. They were able to create a map using the assistance of hashtags that allowed them to gather the information much quicker than if relief workers just ran into the Philippines with no preparation or information [9].

The crowdsourcing involved people from all around the world who viewed satellite images from space and provided relief agencies with their knowledge of the changes that had occurred on the ground after the storm passed. Officials from the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) coordinated the effort to get volunteers to help with the aid relief. Doctors Without Borders received updated maps generated by over 1,000 OpenStreetMap volunteers in 82 countries. They identified hospital locations, which buildings were intact and which were damaged, blocked roads, and other key infrastructure [10].

Technological advances in sensing, computation, storage, and communications will turn the near-ubiquitous mobile phone into a global mobile sensing device. People-centric sensing will help drive this trend by enabling a different way to sense, learn, visualize, and share information about ourselves, friends, communities, the way we live, and the world we live in. It juxtaposes the traditional view of mesh sensor networks with one in which people, carrying mobile devices, enable opportunistic sensing coverage [3].

Since people centric sensing began, content provided by ordinary people, so-called "citizen journalists" or individuals with particular agendas that is posted or shared on Social Networks such as Twitter, YouTube, Facebook, MySpace or Flickr, to name but a few, has increasingly made it into the channels and services of traditional information providers such as news organizations. New and affordable publishing and distribution tools for ordinary citizens such as Social Networks, blogs, or services have made this possible. Social Networks have more and more become an integral part of the communication mix for all kinds of aims, for example (political) campaigning, and awareness-raising [4]. See for example, Fox News revamped its newsroom for Shephard Smith Reporting on breaking news, such as December 2013 shooting at Arapahoe High School in Colorado. Open source data is valuable in order to populate the reward matrices for game theory applications.

III. Game Theory

Current situational awareness efforts seek to incorporate not only geospatial features and structures, but also the human element, especially in urban settings. An attempt to predict the likelihood of human reactions to a future event should be based on correct situational analysis. Development of tools for more rapid refinement of flexible plans is required for adapting to a changing operational environment.

Our solution populates a reward matrix in near real time through powerful game theory analysis. Once data accuracy is proven through sensitivity analysis, the information is can either be used as training data or populated into a reward matrix in real time for resource allocation and adversarial planning utilizing game theory analysis. Our techniques enable a methodical approach to intelligent planning and reaction based upon construction and analysis of a decision model resulting in a structure of the most probable solution. This technique is useful for a number of applications ranging from behavioral economics, war fighter planning, and analysis of information, messaging, and risk management. Our system supports an artificial intelligence (AI) supervised learning approach to quantify information based on user selectable attributes and deriving probabilistic decision outcomes. Our approach trains with near real time execution.

Our solution integrates multiple data sources into efficient intent analysis processes and uses training data to build the decision trees to predict categories for new events based upon classifiers created for the use case scenario. Given an event, we predict a category and then determine sentiment based on trained data. This information could then be applied during planning in support of course of action (COA) development in the military decision making process (MDMP).

The approach combines the following input: open (unstructured) source, and/or direct user input/modification. In particular, we capture and model "sentiment" and other situational factors through the assignment of positive, neutral and negative values. A reward matrix is then populated using game theoretic concepts such as in a competitive game model. GlobalSite utilizes game theory which permits the ability to solve for iterative solutions, instantaneous visual feedback, and interactions by the user on demand. Our output enables a methodical approach to intelligent planning and reaction including interaction of variables, parameters and attributes by user resulting in updated probabilities. Game theory is useful for resource management of manpower, equipment, and warnings, etc., since it shows optimal decision for deployment.

In many situations, the opponents know the strategy that they are following. We assume that the players know what actions are available. A maximin equilibrium often is the strategy and is called the Nash theory application of zero or constant sum strategy game. We also consider a constant sum game in which for both player's strategies, the two player's reward add up to a constant value. This means, while both players are in conflict, that there is more to gain than simply having one player's reward equaling the other player's loss.

We can find optimal strategies for this two-person zero-sum game [24]. For example, if a reward matrix exists, then the equilibrium point is the one where the reward is the smallest value in its row and the largest number in its column. A pure strategy provides a complete definition of how a player will play a game. A player's strategy set is the set of pure strategies available to that player. A mixed strategy is an assignment of a probability to each pure strategy. This equilibrium is also known as the Nash Equilibrium [15].

Game theory is divided into two branches, non-cooperative and cooperative [2]. Algorithms for computing Nash equilibrium are well-studied. N-player games are computationally harder than 2-player games, in important ways such as visualization of the solution [11].

IV. Emergency Response Example

A. *Resource Planning*

In our example, there are several resource management stages or hierarchies as shown in Fig 2. These stages include information needs, collection objectives, observables, tasks and plans. The resource management process seeks to decompose information needed to satisfy mission objectives into one or more tasks. The essence of resource management is uncertainty management [13]. Resource allocation problems in which limited resources must be allocated among several activities are often solved by dynamic or linear programming. Operations Research is a branch of mathematics that studies decision making to obtain the best decision. Game theory can help determine the optimal investment strategy [24].

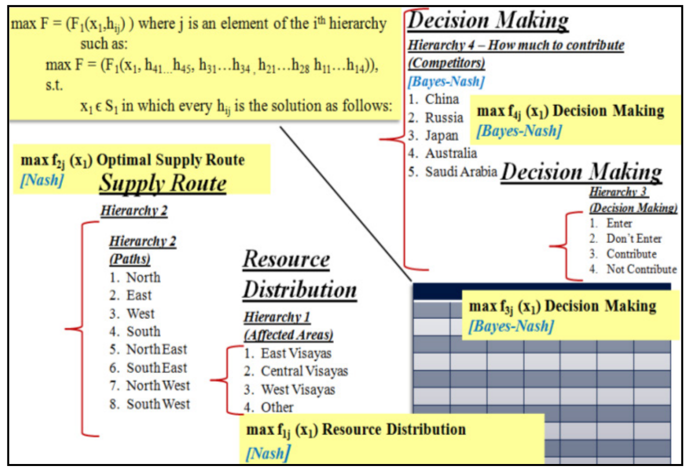

Fig 2. Bayesian Hierarchy

Our solution populates a reward matrix in near real time through powerful game theory analysis. Once data accuracy is proven through sensitivity analysis, the information can either be used as training data or populated into a reward matrix for resource allocation and adversarial planning utilizing game theory concepts such as in a competitive or cooperative game model. Much of the current focus is on human geography and terrain as well as population based sentiment analysis [17].

Objects	Attributes						
	Deaths	Injury	Missing	People Displaced	Damage to Agriculture	Damage to Infrastructure	Aid Needed
Eastern Visayas (Tacloban)	3725	18,175	1598	10K	$40M	$12M	A1
Western Visayas	161	228	19	5K	$20M	$4M	A2
Central Visayas (Cebu)	74	102	5	2K	$5M	$2M	A3
Other Regions	16	24	0	1K	$2M	$1M	A4

Fig 3. Reward Matrix

Figure 3 shows populated example values for a resource planning game. We use the Nash equilibrium to solve for the mixed solutions in a repeatable and methodical manner to determine optimal choices. In our example, open source data is used to create a cost function. In our example using the reward matrix, we show the linear programming solution for the constant sum game as follows:

$$\begin{array}{llllll}
\max v & & & & & \\
\text{s.t. } v - & 372\ x1 - & 16\ x2 - & 7\ x3 - & 2\ x4 & <= 0 \\
v - & 181\ x1 - & 2\ x2 - & 1\ x3 - & 1\ x4 & <= 0 \\
v - & 160\ x1 - & 2\ x2 - & 1\ x3 - & 0\ x4 & <= 0 \\
v - & 100\ x1 - & 50\ x2 - & 20\ x3 - & 1\ x4 & <= 0 \\
v - & 40\ x1 - & 20\ x2 - & 5\ x3 - & 2\ x4 & <= 0 \\
v - & 12\ x1 - & 4\ x2 - & 2\ x3 - & 1\ x4 & <= 0 \\
x1 + x2 + x3 + x4 = 1 & & & & & \\
x1, x2, x3, x4 >= 0 & & & & &
\end{array} \quad (1)$$

Equation (1) is used to determine the best strategy for the blue player to deliver aid. The solution for the blue player's mixed strategy in terms of probabilities x = (1, 0, 0, 0). Figure 4 shows iterative modeling of the situation over time periods in order to optimize decision making. Initially, the best decision is to send aid to Eastern Visayas in accordance with the reward matrix.

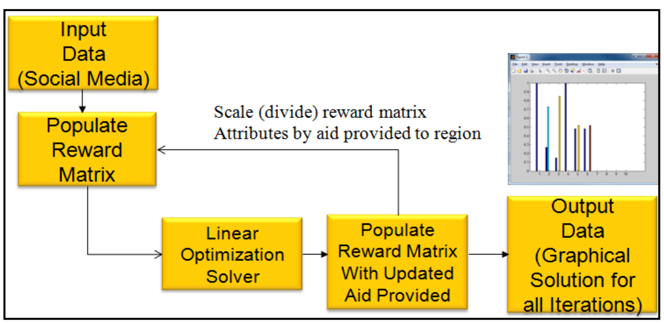

Fig 4. Iterative Modeling

When the reward matrix contains no saddle point, we can use a linear program solver. Some tools use "strategies" measured in different units in the same reward matrix and can be problematic. If all strategies in a given decision model reward matrix are not in the same (equalized) units, then use of game theory and mini-max or maxi-min functions can provide misleading results. We can create purely dominant and incorrect solutions just due to relative size of unit measures. Our solution addresses this properly and uniformly for any decision model. We equalize all strategies (in a given decision model) to the same unit. This is a key point to the application of game strategies to a general class of decision problems. An adjustable "equalization" factor has the purpose to convert all strategy measures to the same unit (e.g., cost, time) and must be done for any decision model. The equalization factor for our solution is independent of additional (importance) weights that may be applied.

Using different weights allowed for choices is to highlight the ability and need for a tool which can be used to allow the user to dial and modify modeled parameters of the reward matrix to model "what if" scenarios. Additionally saving the weights to a file allows for peer review in order to check and validate decisions. Our approach is modeled, so that the process can be repeated to allow for new or higher quality data/information to be inserted into the process to generate updated results.

B. *Path Planning*

Path planning algorithms are commonly used to find the least cost path from a start node to an end node through a gridded environment of cost. The cost of a given node-to-node transit may simply relate to the distance traveled combined with some measure of an obstruction. This allows the algorithm to find the shortest path through a maze for example. Given a weighted directional graph with a start node and a set of end nodes, the optimal path problem is to find a least-cost path from start to any member of end, where the cost of the path may, in general, be an arbitrary function of weights assigned to nodes and branches along path.

Our algorithm applies an additive evaluation function:

$$f(n) = ct(n) + \mathrm{s}(n) + e(n) + \mathrm{h}(n) + d(n) \quad (2)$$

where $ct(n)$ is the cost of terrain movement due to damage to infrastructure evaluated along dynamic path in north direction. The safety value $s(n)$ is the cost of the safety along dynamic path in north direction. Elevation information value $e(n)$ derived from SRTM or LiDAR data is the cost in the dynamic path in the north direction. The hospital presence value $h(n)$ is the cost in the dynamic path in the north direction. The distance value $d(n)$ is the minimum possible cost to reach the end from a given node and is a crucial component of the algorithm. It drives the algorithm towards the end node. It should be noted that $f(e)$,$f(w)$ and $f(s)$ correspond to nodes in the east, west, and south directions respectively.

In order to avoid a combinatorial explosion of potential paths, the algorithm, and therefore target motion, is restricted to a gridded environment of nodes. This also ensures that the same node may be revisited from a different direction allowing for the best path to be continuously updated. The distance between nodes should be as large as possible in order to minimize the number of nodes that must be expanded, thereby reducing computation time, while not impacting on the solution [23].

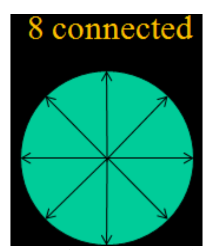

Fig 5. Eight Connected Movement Direction Methods

The resolution of the grid we chose is 90 meters on a side. Figure 5 shows two possible movement methods through the grid. The eight connected method lets the user travel diagonally. This does mean extra compute time per movement, but yields more realistic results. The goal is to minimize cost of traveling along an optimal path. We are seeking a minimum cost function from the reward matrix shown in Table 1, with eight connected movements.

Table 1. Reward Matrix

	Cost of Terrain Movement from Damage	Elevation Information	Safety (Police, Command Post) Presence	Hospitals (Presence)	Distance to Drop Off Center
Blue Player Choice #1 (move north)	ct(n)	e(n)	s(n)	h(n)	d(n)
Blue Player Choice #2 (move north east)	ct(ne)	e(ne)	s(ne)	h(ne)	d(ne)
Blue Player Choice #3 (move east)	ct(e)	e(e)	s(e)	h(e)	d(e)
Blue Player Choice #4 (move south east)	ct(se)	e(se)	s(se)	h(se)	d(se)
Blue Player Choice #5 (move south)	ct(s)	e(s)	s(s)	h(s)	d(s)
Blue Player Choice #6 (move south west)	ct(sw)	e(sw)	s(sw)	h(sw)	d(sw)
Blue Player Choice #7 (move west)	ct(w)	e(w)	s(w)	h(w)	d(w)
Blue Player Choice #8 (move north west)	ct(nw)	e(nw)	s(nw)	h(nw)	d(nw)

It is acceptable to model a player's choice of strategies with probabilities. A game with a randomized (or mixed) strategy is one in which all of a player's choices add up to a value of one. A mixed strategy is comprised of possible actions and an associated probability. Any mixed strategy that guarantees an expected reward at least equal to the value of the game is an optimal strategy [24]. Our model's possible choices of movement are:

x_1 = *probability that blue player chooses north*
x_2 = *probability that blue player chooses north east*
x_3 = *probability that blue player chooses east*
x_4 = *probability that blue player chooses south east*
x_5 = *probability that blue player chooses south*
x_6 = *probability that blue player chooses south west*
x_7 = *probability that blue player chooses west*
x_8 = *probability that blue player chooses north west*

Our example can be considered a game in which the red player, or nature, has already placed obstacles due to destruction in the path of the blue player and now it is the blue player's responsibility to navigate through the scene as shown in Figure 6. Our solution is dynamic since decisions of movement are made at every point on the grid along the path. The solution for the blue player's mixed strategy in terms of probabilities $x = (n, ne, e, se, s, sw, w, nw)$. We can solve this linear program using several techniques such as the simplex method, the dual simplex method, or the artificial basis technique. To show how our system could work, we utilized a computer with LINGO software to solve for the mixed strategies as well as the value of the game. We apply the reward matrix to every grid point value from start to end. The path from the south is in yellow, in Fig 7a.

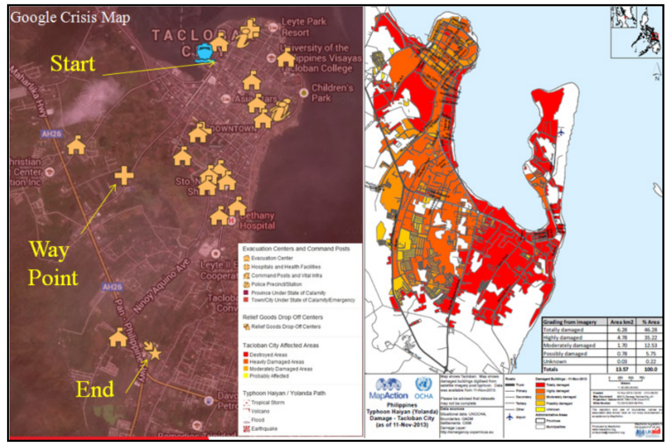

Fig 6. Optimal Path to Drop Off Center

More than one million Tweets and text messages were tapped and then mapped using MicroMappers, applications designed for disaster response. In Tacloban, the city that bore a direct assault from Haiyan's storm surge, 58% of the built up areas were destroyed or damaged. In the image below you can see orange, red and yellow color-keyed buildings. The orange, shown in Fig 7b, represent seriously damaged structures. The red indicates buildings that were completely destroyed. The yellow are buildings largely intact [10].

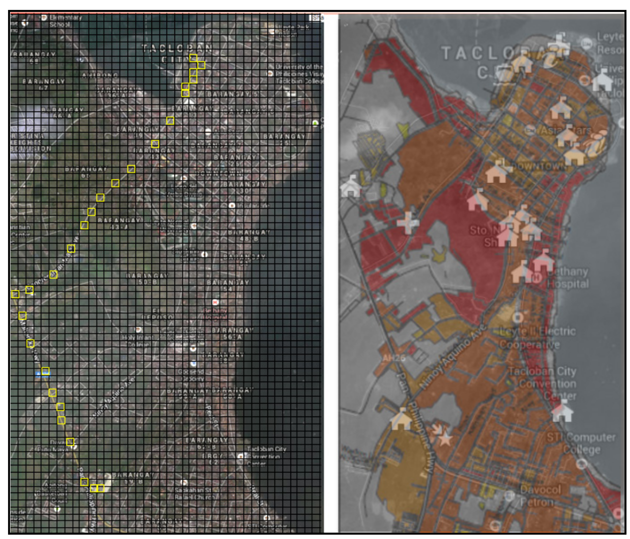

Fig 7.a Optimal Path to Drop Off Center b. Damage Areas

Our solution uses a Markov processes since the current state depends only on a finite history of previous states. For the first-order Markov process we have:

$$p(r_k|\{r_0, r_1, ..., r_{k-1}\}) = p(r_k|r_k-1) \qquad (3)$$

where r is the pixel to be labeled along the traversed path and k is time. In a Markov Chain we define transition probabilities as the probability that the system is in state i at time k when in state j at time k-1 [21]. In our Hidden Markov Model (HMM) problems we have modeled our transition probabilities as calculated from the Nash Equilibrium.

During the traversal along dynamic path, if a repeat of path is encountered, then we use next highest mixed strategy probability direction in order to prevent an infinite loop from occurring. Our current solution only looks one step ahead. We also have accounted for a rescaling of the weights in the reward matrix if the algorithm gets stuck in a loop.

Our Markov Decision Process is a sequential decision problem defined by a state set S, and an action A. The efficiency, for the blue player, of the algorithms is determined using the following formula [18]:

$$\text{Efficiency} = \frac{Length\ of\ final\ path}{Number\ of\ Cells\ Searched} \text{ x } 100 \qquad (4)$$

Recent advances in self-supervised learning have enabled very long-range visual detection of obstacles and pathways (to 100 hundred meters or more). Unfortunately, the category and range of regions at such large distances come with a considerable amount of uncertainty. A mapping and planning system that accurately represents range and category uncertainties, and accumulates the evidence from multiple frames in a principled way are desired [19].

C. *Bayesian Decision Making*

When a natural disaster occurs, one of the first decisions that a country or player makes is whether or not to participate or enter into the game. This is called an entry game. Another question which occurs is the how much commitment in terms of contribution is desired. Models decisions may be based on the toughness of the incumbent.

A large class of sequential decision making problems under uncertainty with multiple competing decision makers/agents can be modeled as stochastic games. Non-cooperative games can be solved in which each decision maker makes his own decision independently and each has an individual payoff function. In stochastic games, the environment is non-stationary and each agent's payoff is affected by joint decisions of all agents, which results in the conflict of interest among decision makers [12]. Nash Equilibrium game theory considers the effect of a player's decision on other decision makers [13].

Bayesian game is an interactive decision situation involving several decision makers (players) in which each player has beliefs about (i. e. assigns probability distribution to) the payoff relevant parameters and the beliefs of the other players. It is convenient to think of a state of nature as a full description of a 'game-form' (actions and payoff functions). Type also known as state of mind, is a full description of player's beliefs (about the state of nature), beliefs about beliefs of the other players, beliefs about the beliefs about his beliefs, etc. ad infinitum. State of the world is a state of nature and a list of the states of mind of all players [25].

Game theory, as a model of conflict, suffers from several limitations. Players are assumed to always maximize their outcomes. Not all of the payoffs or situations can be quantified in a reward matrix. Game theory is not applicable to all types of problems. However, game theory offers important insights and demonstrates superiority of cooperation over competition. Game theory models the heuristics people use in managing their conflicts and helps to explain why rational decisions often miss opportunities for mutual gain [16].

Imperfect information may still be useful to help make decisions. Opponent modeling works by observing the opponent's actions and building a model by combining information from a pre-computed equilibrium strategy with the observations [5]. Previous work performed in the community includes computing robust optimization equilibrium by methods analogous to those for identifying Nash Equilibrium of a finite game with complete information [1].

There is much attention given to simultaneous-move, one-shot, normal form games with complete information. Each player or agent has a private payoff known only to that agent. The payoff to an agent x is not only a function of all the agents' actions (as in the usual complete information game) but also of the realized private-type of agent x. The type of an agent may be discrete or continuous. Each agent's realized type is chosen independently from some commonly known distribution over types, and the payoff matrices for the agents are also common knowledge. These games have incomplete information because each agent must choose its strategy, i.e., its probability distribution over its actions, without knowing the realized types of all the other agents [20].

Harsanyi proposed a method for transforming uncertainty over the strategy sets of players into uncertainty over their payoffs. The transformation appears to rely on an assumption that the players are rational. Without a common belief of rationality, such implications are not necessarily maintained under a Harsanyi transformation. Under the belief system model, such implications can be maintained in the absence of common belief of rationality [6].

Generally, players may not possess full information about their opponents. In particular, players may possess private information that others should take into account when forming expectations about how a player would behave. To analyze these interesting situations, a class of games with incomplete information was created as use case scenarios (i.e., games where at least one player is uncertain about another player's payoff function) which are the analogue of the normal form games with complete information similar to Bayesian games (static games of incomplete information) [22].

Several studies provide discussion and attempts to integrate and validate usefulness of the application of game theory models. The strategy action game is not only applicable in the field of commercial negotiation; subsequent research can extend further into the fields of education, marketing, finance, risk management, and society. The competition and cooperation relationship between manufacturer and distributor in other applications are delicate, allowing room for other methods besides strategy action game, such as series bargaining game and mean difference. Studies have been performed on the analysis aiming at the strategy application, and intervention into the negotiation harmonization with the manufacturer or distributor. On one hand, it insists on an objective observation attitude; on the other, it may also produce the deviation of unscrambling the behavior of game participants subjectively [14]. In our example, let:

P(U) = Probability of United States Giving
P(¬U) = Probability of United States Not Giving
P(S) = Probability of Saudi Arabia Giving
P(¬S) = Probability of Saudi Arabia Not Giving

$$P(U|S) = \frac{P(S|U)(P(U)}{P(S)}$$

$$P(U|S) = \frac{P(S|U)P(U)}{P(S|U)\,P(U) + P(S|\neg U)P(\neg U)}$$

Using event space, j = {give, not give},

$$P(U|S) = \frac{P(S|U)P(U)}{\sum j\, P(S|Uj)\, P(Uj)}$$

Suppose a country receives an update about a situation, i, and interprets the information as motivation for giving aid, the probability of a country not giving when there is a desire for future cooperation with the Philippines is:

$$P(\neg U|i) = \frac{P(i|\neg U)P(\neg U)}{P(i|\neg U)P(\neg U) + P(i|U)P(U)}$$

- Let p = probability of not giving with *no desire* for future cooperation
- Let r = probability of giving with *desire* for future cooperation
- Let q = probability of not giving (historical)

$$P(\neg U|i) = \frac{(1-p)q}{(1-p)q + r(1-q)}$$

The country's payoffs are:

- 0, -if not give and do not desire help in future
  -if give and desire help in future
- -z, -if not give and desire help in future
- -(1-z), -if give and do not need help in future
- z is cost of missing opportunity for giving (type I error),
- 1 - z -cost of giving without future benefit (type II error).

We model that a country will give if $(1\text{-}z)P(\neg U|i) \leq z(1\text{-}P(\neg U|i))$:

$$z \geq P(\neg U|i) = \frac{(1-p)q}{(1-p)q + r(1-q)}$$

We model that a country will not give if:

$$z \leq P(\neg U|i) = \frac{pq}{pq + (1-r)(1-q)}$$

A country optimally acts according to interpretation of situational awareness information as motivation for giving.

$$\frac{pq}{pq + (1-r)(1-q)} \leq z \leq \frac{(1-p)q}{(1-p)q + r(1-q)}$$

If another country is not motivated to give, then a country may not be as motivated to give (or give as much):

$$P(\neg U|i, \neg i) = \frac{P(i,\neg i|\neg U)P(\neg U)}{P(i,\neg i|\neg U)P(\neg U) + P(i,\neg i\,|U)P(U)}$$

$$P(\neg U|i, \neg i) = \frac{(1-p)pq}{(1-p)pq + r(1-r)(1-q)}$$

Let n = the number of countries. A country will give if [7]:

$$z \geq \frac{(1-p)p^{n-1}\,q}{(1-p)p^{n-1}\,q + r(1-r)^{n-1}(1-q)}$$

$$z \geq \frac{1}{1+[r/(1-p)][(1-r)/\,p)^{n-1}\,]([1-q)/q]} \qquad (5)$$

Given that p > 1-r, and p > 1/2 > 1 – q, the denominator approaches 1 as n increases. Therefore, as n increases, if countries are motivated even slightly to give when there is no need without future benefit (type II error), then a country who interprets a piece of information as motivation for giving will nevertheless not give. Our model indicates that a country is less concerned about giving when there are multiple n givers. In this Nash Equilibrium the probability of a country not giving increases as n increases. Figure 8 shows a plot of z values with decreasing values for z as n increases using Equation 5. As q decreases, the value of z increases.

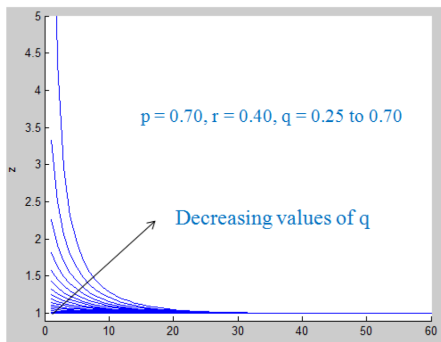

Fig 8. Plot of z values vs. n players

Figure 9 shows the reward matrix of aid provided for countries competing for good will towards Philippines. Solving the reward matrix using a Bayes-Nash solver shows that the United States is best choice for Philippines as a national strategic ally.

Countries	Attributes			
	Humanitarian AID	Medical Team	Humanitarian Goods	Troops
United States (USAID/DoD)	$55M	Yes	Yes	1600
Saudi Arabia	$10M	No	No	0
Japan	$54M	Yes	Yes	1000
China	$2M	Yes	Yes	0
Russia	$1.2M	Yes	No	0
Australia	$31M	Yes	No	0

Fig 9. Adversarial Planning

V. Conclusion

No decision is ever 100% correct; however, understanding the effects of algorithmic decisions based upon multiple variables, attributes, or factors and strategies with probability assignments can increase the probability for the best decision for a particular situation or event. GlobalSite can perform open source discovery and data mining activities to parse information found from disparate, non-obvious, and previously unknown data sources and allows for the user to dial the weighting factors based upon their knowledge or expertise.

We discussed a method for modeling asset management with limited resources. We realize that solution presented is only a guide and is not intended to replace the human brain in decision making. We offer a user assisted means of prioritization to make agent and resources more effective. Automated game theory is promising for automatically solving real world strategies and helps the security analyst make optimal decisions for target tracking and detection activities. Automated processing techniques are needed to augment tactical intelligence-analysis capabilities by identifying and recognizing features of obstruction.

We have identified a mathematical application using linear programming optimization. Our solution provides the ability to populate a reward matrix from remotely sensed data. We calculate optimal strategies for path optimization which increases likelihood of best decision available using game theory in a constant sum game. We combine a number of technologies for data fusion/ visualization. Our solution is a multi-use application: course of action (COA) planning, strategies, resource management, risk assessment, etc.

Automated processing techniques are needed to augment tactical intelligence-analysis capabilities by identifying and recognizing patterns, weighting them appropriately, providing near real time objective decisions where the user can interact with the information based upon their experiences and knowledge base. GlobalSite is a probabilistic decision solution which allows for users to interact with information in near real time using game theory to provide a reward matrix of the best possible outcomes.

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