Pontifícia Universidade Católica
do Rio de Janeiro

Raissa Zurli Bittencourt Bravo

The use of UAVs in humanitarian relief: a POMDP based methodology for finding victims

Dissertação de Mestrado (Opção acadêmica)

Thesis presented to the Programa de Pós-Graduação em Engenharia de Produção of the Departamento de Engenharia Industrial, PUC-Rio, as partial fulfillment of the requirements for the degree of Mestre em Engenharia de Produção – opção acadêmica.

Advisor: Profª. Adriana Leiras

Co-advisor: Prof. Fernando Cyrino

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Profª. Adriana Leiras
Advisor
Departamento de Engenharia Industrial - PUC-Rio

Prof. Fernando Cyrino
Co-advisor
Departamento de Engenharia Industrial - PUC-Rio

Prof. Roberto Cintra Martins
Departamento de Engenharia Industrial - PUC-Rio

Profª. Luciana de Souza Pessoa
Departamento de Engenharia Industrial - PUC-Rio

Prof. Márcio da Silveira Carvalho
Coordinator of the Centro Técnico Científico da PUC-Rio

Rio de Janeiro, February 25th, 2016

Raissa Zurli Bittencourt Bravo

Raissa Zurli Bittencourt Bravo graduated in Industrial Engineer at Pontifícia Universidade Católica do Rio de Janeiro, PUC-Rio, in 2013. She worked during three years with project management. Since 2013 she works on her IT family business.

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Abstract

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The use of Unmanned Aerial Vehicles (UAVs) in humanitarian relief has been proposed by researchers for searching victims in disaster affected areas. The urgency of this type of operation is to find the affected people as soon as possible, which means that determining the optimal flight path for UAVs is very important to save lifes. Since the UAVs have to search through the entire affected area to find victims, the path planning operation becomes equivalent to an area coverage problem. In this study, a methodology to solve the coverage problem is proposed, based on a Partially Observable Markov Decision Processes (POMDP) heuristic, which considers the observations made from UAVs. The formulation of the UAV path planning is based on the idea of assigning higher priorities to the areas which are more likely to contain victims. The methodology was applied in two illustrative examples: a tornado in Xanxerê, Brazil, which was a rapid-onset disaster in April 2015 and a refugee's camp in South Sudan, a slow-onset disaster that started in 2013. After simulations, it is demonstrated that this solution achieves full coverage of disaster affected areas in a reasonable time span. The traveled distance and the operation's durations, which are dependent on the number of states, did not have a significative standard deviation between the simulations. It means that even if there were many possible paths, due to the tied priorities, the algorithm has homogeneous results. The time to find groups of victims, and so the success of the search and rescue operation, depends on the specialist's definition of states priorities. A comparison with a greedy algorithm showed that POMDP is faster to find victims while greedy's performance focuses on minimizing the traveled distance. Future research indicates a practical application of the methodology proposed.

Keywords

humanitarian relief; disaster; UAVs; drones; POMDP; simulation

Resumo

Bravo, Raissa Zurli Bittencourt; Leiras, Adriana. **O uso de VANTs em ajuda humanitária: uma metodologia baseada em POMDP para encontrar vítimas.** Rio de Janeiro, 2016. 89p. Dissertação de Mestrado – Departamento de Engenharia Industrial, Pontifícia Universidade Católica do Rio de Janeiro.

O uso de Veículos Aéreos Não Tripulados (VANTs) na ajuda humanitária tem sido proposto por pesquisadores para localizar vítimas em áreas afetadas por desastres. A urgência desse tipo de operação é encontrar pessoas afetadas o mais rápido possível, o que significa que determinar a roteirização ótima para os VANTs é muito importante para salvar vidas. Como os VANTs tem que percorrer toda a área afetada para encontrar vítimas, a operação de roteirização se torna equivalente a um problema de cobertura. Neste trabalho, uma metodologia para resolver o problema de cobertura é proposta, baseada na heurística do Processo de Decisão de Markov Parcialmente Observável (POMDP), onde as observações feitas pelos VANTs são consideradas. Essa heurística escolhe as ações baseando-se nas informações disponíveis, essas informações são as ações e observações anteriores. A formulação da roteirização do VANT é baseada na ideia de dar prioridades mais altas às áreas mais propensas a terem vítimas. Para aplicar esta técnica em casos reais, foi criada uma metodologia que consiste em quatro etapas. Primeiramente, o problema é modelado em relação à área afetada, tipo de drone que será utilizado, resolução da câmera, altura média do voo, ponto de partida ou decolagem, além do tamanho e prioridade dos estados. Em seguida, a fim de testar a eficiência do algoritmo através de simulações, grupos de vítimas são distribuídos pela área a ser sobrevoada. Então, o algoritmo é iniciado e o drone, a cada iteração, muda de estado de acordo com a heurística POMDP, até percorrer toda a área afetada. Por fim, a eficiência do algoritmo é testada através de quatro estatísticas: distância percorrida, tempo de operação, percentual de cobertura e tempo para encontrar grupos de vítimas. Essa metodologia foi aplicada em dois exemplos ilustrativos: um tornado em Xanxerê, no Brasil, que foi um desastre de início súbito em Abril de 2015, e em um campo de refugiados no Sudão do Sul, um desastre de início lento que começou em 2013. Depois de fazer simulações, foi demonstrado que a solução cobre toda a área afetada por desastres em um período de tempo razoável. A distância percorrida pelo VANT e a duração da operação, que dependem do número de estados, não

tiveram um desvio padrão significativo entre as simulações, o que significa que, ainda que existam vários caminhos possíveis devido ao empate das prioridades, o algoritmo tem resultados homogêneos. O tempo para encontrar grupos de vítimas, e portanto o sucesso da operação de resgate, depende da definição das prioridades dos estados, estabelecidas por um especialista. Caso as prioridades sejam mal definidas, o VANT começará a sobrevoar áreas sem vítimas, o que levará ao fracasso da operação de resgate, uma vez que o algoritmo não estará salvando vidas o mais rápido possível. Ainda foi feita uma comparação do algoritmo proposto com o método guloso. A princípio, esse método não cobriu 100% da área afetada, o que tornou a comparação injusta. Para contornar esse problema, o algoritmo guloso foi forçado a percorrer 100% da área afetada e os resultados mostram que o POMDP tem resultados melhores em relação ao tempo para salvar vítimas. Já em relação a distância percorrida e tempo de operação, os resultados são iguais ou melhores para o POMDP. Isso ocorre porque o algoritmo guloso tem o viés de otimizar distância percorrida e, logo, otimiza o tempo de operação. Já o POMDP tem como objetivo, nesta dissertação, salvar vidas e faz isso de forma dinâmica, atualizando sua distribuição de probabilidades a cada observação feita. O ineditismo desta metodologia é ressaltado no capítulo 3, onde mais de 139 trabalhos foram lidos e classificados com o intuito de mostrar quais são as aplicações que drones em logística humanitária, como o POMDP é usado em drones e como a técnica de simulação é utilizada em logística humanitária. Apenas um artigo propõe o uso de POMDP em operações de resgate com drones mas não aplica a técnica a casos reais. Pesquisas futuras podem aplicar a metodologia em desastres em áreas maiores, o que tornará necessário o uso de mais de um drone, pois a autonomia passará a ser uma restrição em termos de distância percorrida e tempo de operação. Outra sugestão é a aplicação da metodologia proposta em casos reais já que os pequenos VANTs são programáveis. Nesse caso, o experimento deve ocorrer em terrenos privados ou em áreas militares, para atender aos requisitos legais.

Palavras-chave

ajuda humanitária; desastre; VANTs; drones; POMDP; simulação

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1 Introduction

One of the most significant difficulties facing United Nations (UN) Agencies and Non-Governmental Organizations (NGOs) when responding to rapid onset disasters, like floods, earthquakes and hurricanes, is to understand the requirements of the affected population accurately and swiftly. Current direct assessment methods are time consuming and the data captured is often not conducted in a systematic way with the locations sampled not being geographically representative (too clustered and too few), and the subsequent reports being produced too late (TATHAM, 2009).

Unmanned Aerial Vehicles (UAVs), or drones, have been used in humanitarian response since 2001, after the terrorist attack of 9/11. An unprecedented number of small and lightweight UAVs were launched in the Philippines after Typhoon Haiyan in 2013, in Haiti following Hurricane Sandy in 2012 and, more recently, they were flown in response to the massive flooding in the Balkans and after the earthquake in China (MEIER, 2014).

UAV refers to a class of aircrafts that can fly without the onboard presence of a pilot. They can be flown by an electronic equipment adapted to the vehicle and on a GCS (Ground Control Station), or directly from the ground. In this last case, it is common to associate the system with the expression RPV (Remotely Piloted Vehicle), since the vehicle is remotely piloted and operated by radio-controlled devices. In the literature, other terms also indicate such category of vehicles, such as: Drone, ROA (Remotely Operated Aircraft), UVS (Unmanned Vehicle System) and UAS (Unmanned Aerial System) (BENDEA *et al.*, 2008).

According to Hall and Coyne (2014), world governments spent more than $6.6 billion on “drone” technology in 2012. This number is expected to increase to $11.4 billion a year over the next decade for a worldwide UAV market worth more than $89 billion.

The increased demand for drone technology following the Gulf conflict was augmented substantially by the post-9/11 conflicts, in Afghanistan and Iraq. These conflicts, coupled with the broader Global War on Terror, created an opening for the expanded use of drones on an unprecedented scale. Figure 1 shows the Department of Defense spending on UAS (HALL; COYNE, 2014).

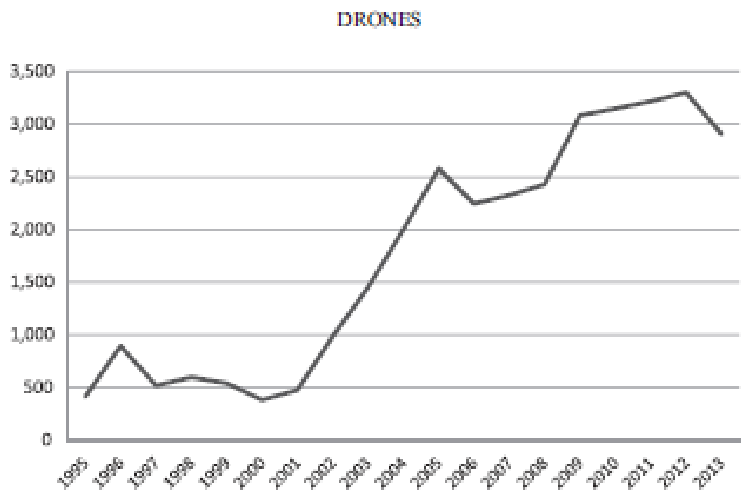

Figure 1: DOD spending on UAS: 1995–2013 (in million US$)

Source: Hall and Coyne (2014)

The UAV view from above is central for humanitarian response as they can capture aerial imagery at a far higher resolution, more quickly and at much lower cost than the satellite imagery. Unlike satellites, members of the public can actually own UAV, which means that disaster-affected communities can respond to a crisis (MEIER, 2014).

In recent years, mobile sensors have been successfully adopted for terrestrial and ocean monitoring. The next logical step in their evolution is to enable mobile sensors to explore the aerial dimension, i.e., engineering small and medium sized UAVs with sensors and wireless radios to form an Aerial Wireless Sensor Network (AWSN). AWSNs are being increasingly used in a variety of applications, such as search and rescue operations, which can benefit significantly from the use of AWSNs to survey the affected area (often very large) and collect evidences about the presence and possible victims' locations. Manned rescue teams can be effectively directed to these locations to maximize the possibility of rescuing trapped victims (MURTAZA *et al.*, 2013).

An important step for the success of the search and rescue mission is the process of path planning, i.e., designing the autonomous flight path of the UAVs. In most practical disaster situations, the number of trapped victims is unknown. As such, the path planning operation becomes equivalent to an area coverage problem, since the UAVs have to search through the entire affected area to find the victims. Moreover, in typical disaster areas, certain locations are more likely to have stranded victims. Hence, if the UAVs are programmed to first visit such locations, then it is likely that the stranded victims will be found quickly. In this work, a priority based approach is adopted for coverage path planning in UAVs networks. Different priorities are assigned to different regions within the target area based on a priori knowledge of the terrain (MURTAZA *et al.*, 2013).

Cormen *et al.* (2001) study the coverage problem as an optimization problem that models many feature selection problems. Their corresponding decision problem generalizes the NP-Complete vertex coverage problem and therefore is also NP-Hard. A significant work on coverage is also performed by Zheng *et al.* (2010). They first show that weight minimal coverage using K mobile robots is NP-Complete. Then they provide an approximate solution based on spanning tree. The constrained coverage problem is different from weight minimal coverage problem. An optimal weight minimal solution can have a path that has minimal weight. However, it can be the case that the cell with highest priority is visited at the end. To overcome this issue, in this dissertation we propose a Partially Observable Markov Decision Process (POMDP) based solution for the constrained coverage problem. It has been shown that POMDP can provide an optimal policy to move from the starting position to the highest priority area in order to maximize the reward (MURTAZA *et al.*, 2013). Motivated by this, a POMDP based solution to guide individual UAVs to high priority areas is proposed.

According to Cassandra (1998b), POMDPs can be used to model problems in very different areas: machine maintenance, robots navigation, elevators controllers, computer vision, behavior modeling ecosystems, military applications, medical diagnosis, education and other areas. Some notable cases of applications are the Hauskrecht (1997) work, with the modeling of heart ischemic diseases. Pineau (2004) used POMDP for modeling a robot behavior to help old people to remember their commitments, follow them and guide (in a limited way) their dialogs. Poupart (2005) implemented a system that follows patient’s behavior with dementia, monitoring them with a camera and helping them to wash their hands.

Lots of researchers have proposed using UAVs for assistance in post disasters operations. In this type of operation, the path planning task is determinant for saving victim’s lifes. There are many techniques proposed for path planning in the literature. Daniel *et al.* (2011) have proposed different techniques for coverage, connectivity and exploration, comparing them. However, they have not used the initial belief about the area, at all. A dynamic algorithm based on geometry is proposed by Yanmaz and Bettstetter (2010) but they have not done the redundancy analysis for their algorithm. They do not assume any prior knowledge, which gives the reason for not doing redundancy based analysis. All of these algorithms do not consider the partial observability of the images generated from UAVs (Murtaza *et al.*, 2013).

The key contributions of this study can be summarized as:

- An innovative methodology to find victims in post-disaster affected areas with illustrative examples. A systematic literature review about the applications of UAVs in humanitarian relief did not present any study with this purpose. Humanitarian relief is a recent and growing area but only one author of this area is studying the use of drones in emergency situations.
- The formulation of a path planning problem for UAVs in humanitarian operation as a constrained coverage problem. The constraint is based on the idea of assigning higher priorities to the areas that are more likely to contain victims.
- A heuristic method that uses POMDP as basis and solves the problem of coverage using UAVs.
- The application of the proposed solution in two illustrative examples where the efficacy of the path planning has been demonstrated.

The remainder of this text is organized as follows. Chapter 2 presents the framework of the POMDP technique, Chapter 3 presents a literature review about the applications of UAVs in humanitarian relief, the use of simulation in humanitarian logistics and the POMDP's solution to UAVs. Next, the methodology to formulate the path planning problem is presented on chapter 4. Chapter 5 presents two illustrative examples using POMDP to generate an UAV path planning. The concluding remarks are in chapter 6.

2 Partially Observable Markov Decision Process

This chapter presents the POMDP framework, a technique which will be used in the chapters 4 and 5 to generate the path planning for the drones.

The Markov Decision Process (MDP) framework models a controlled stochastic process with perfectly observable states. It represents the situation in which a control agent can be uncertain about possible outcomes of its actions, but still be able to verify the resulting state once the action is completed. That is, there is no uncertainty regarding to the state the agent currently is, though there is an uncertainty regarding the location where it can be after the next action (Hauskrecht, 1997).

Imagine the situation in which the agent cannot observe the process state directly, but only indirectly through a set of noisy or imperfect observations. The feature of partial observability can be important in many real world problems. For example, a robot planning its route or deciding about what action to take usually works with noisy sensory information; in the medical area, the physician often needs to decide about the treatment based on available findings and symptoms while being uncertain about an underlying disease. In such cases, the perceptual information need not to align with and imply the actual world state with certainty. Then the agent that acts in environments with imperfect state information may face uncertainty from the two sources (Hauskrecht, 1997):

- uncertainty on the action outcome;
- uncertainty on the world state due to imperfect (or partial) information.

Observations may not be costless. Often they can require a special action to be taken before they are available and this action might have both cost or transitional effect. The actions that enable observations are called investigative actions. The main purpose of performing investigative actions is to narrow the uncertainty about the world state, for example, by performing a special test revealing more information about the ongoing patient's disease process, or using camera surveillance in order to detect the current position of the robot. Therefore, when making the decision about an investigative action one needs to carefully consider both benefits and costs associated with performing it. For example, some investigative actions in medicine although very helpful in diagnosing underlying problems can be very risky and costly due to their invasiveness (Hauskrecht, 1997).

The presence of partial observability in the environment, as well as the capability of an agent to perform investigative actions, have a major impact on how the procedure must work. The reason for this is that (Hauskrecht, 1997):

- in order to find an optimal control one should account for imperfect observability now and in future steps;
- during planning, one must consider the cost and benefits of both control and investigative actions.

The main distinction between fully observable MDPs and POMDPs is in the information one uses to select an action. In the MDP case actions are selected using process states that are always known with certainty, while for the POMDP, actions are based only on the available information that consists of previous observations and actions. Note that the observation model as defined makes it possible to condition observations on both actions and process states. This allows one to model investigative actions in the same way as other control actions (Hauskrecht, 1997).

Partially observable Markov decision processes (POMDPs) were first introduced in the control theory and operations research communities as a framework to model stochastic dynamical systems and to make optimal decisions. This framework was later considered by the artificial intelligence community as a principled approach to planning under uncertainty. Compared to other methods, POMDPs have the advantage of a well-founded theory. They can be viewed as a special (continuous) case of the well-known fully observable Markov decision process (MDP) model, which is rooted in probability theory, decision theory and utility theory (Poupart, 2005).

Hsiao *et al.* (2007) provide a method for planning under uncertainty for robotic manipulation by partitioning the configuration space into a set of regions that are close under compliant motions. Hoey *et al.* (2007) present a real-time system to assist people with dementia during handwashing that combines a flexible object tracker with monitoring and decision making using a POMDP. Pineau *et al.* (2003) describe a mobile robotic assistant, developed to assist elderly individuals with mild cognitive and physical impairments, as well as support nurses in their daily activities. Kim *et al.* (2008) present experiments that investigated the effect of the user model on POMDP-based dialogue systems and showed that POMDP strategies significantly outperform MDP strategies. Thomson *et al.* (2008) present the results of a comparative user evaluation of various approaches to dialogue management and the major contribution is a comparison of traditional systems against a system that uses a Bayesian Update of Dialogue State approach.

The focus of the following section is the modelling framework that represents action under nondeterminism, imperfect observability as well as investigative actions. The modelling framework called POMDP is best viewed as a further extension of the MDP framework.

2.1 Model Description

According to Hauskrecht (1997), POMDP is defined as a tuple (S, A, T, R, Ω, O, z, γ) where:

- S is a set of possible states for the stochastic process;
- A is a set of actions that can be executed in different decision times;
- $T : S\ x\ A\ x\ S \rightarrow [0, 1]$ is a function that gives the probability of the system to pass to a s' state, considering it was in state s and action a was executed;
- $R : S\ x\ A \rightarrow \mathbb{R}$ is a function that gives the cost (or reward) for taking a decision a when the process is in s;
- Ω is a set of observations obtained in each decision time;
- $O : S\ x\ A\ x\ \Omega \rightarrow [0, 1]$ is a function that gives the probability of an o observation be verified, considering a s state and an a previous executed action;
- z is the number of time-steps the agent must plan. It is also called "horizon" and can be finite, when there is a fixed number of decision to make, or infinite, when the decision making is made repeatedly;
- γ is a discount factor used to indicate how rewards earned at different time-steps should be weighted. In general, the more lagged a reward is, the smaller its weight will be. Therefore, γ is a constant in [0,1] indicating how a reward should be scaled down for every time-step delay. In this thesis, a reward earned k steps in the future is scaled down by γ^k (Poupart, 2005).

Unless otherwise indicated, this thesis assumes infinite horizon POMDPs with a discount factor strictly less than 1.

The major difference between MDP and POMDP models is that in the POMDP model the underlying process state is not known with certainty and can be only guessed based on past observations, actions and any prior information available. Therefore, one needs to differentiate between the true process state and the information (or perceived) state that captures all things important and known about the process (Hauskrecht, 1997).

2.2 Information State

An information state I_t represents all information available to the agent at the decision time that is relevant for the selection of the optimal action. The information state consists of either a complete historical series of actions and observations or its sufficient statistic. The main reason to use sufficient information states is that they can be significantly smaller and of non-expanding dimension and still allow one to compute optimal value and control functions (Hauskrecht, 1997).

A sequence of information states defines a Markov controlled process in which every new information state is computed as a function of the previous information state, step action and new observations. The equation (1) describes the information state:

$$I_t = \tau(I_{t-1}, o_t, a_{t-1}) \tag{1}$$

where I_t and I_{t-1} denote new and previous information states, and τ is the information state estimator. The process defined over information states is also called the information-state Markov decision process or information-state MDP. In principle, one can always reduce the original POMDP into the information-state MDP (Hauskrecht, 1997).

2.3 Belief States as Sufficient Information States

The quantity often used as a sufficient statistic for planning and control in POMDPs is the *belief state* (or *belief vector*), $b_t(s)$. The belief state assigns probability to every process state and reflects the extent to which states are believed to be present. The belief vector $b_t(s)$ represents the probabilities of the process to be in the state s, at time t, given the information state, as shown in equation (2):

$$b_t(s) = P(s|I_t^c) \tag{2}$$

where I_t^c is a complete information vector at time t.

The major advantages of a belief information state are that it is defined over a finite number of process states and that it is relatively easy to work with. Although one cannot guarantee that a belief state corresponds to the sufficient information vector for an arbitrary POMDP model, a large number of POMDP models used in practice (including standard POMDPs) falls into the class of *belief space POMDPs* (Hauskrecht, 1997).

2.4 POMDP Models

A POMDP model can be converted into an information state MDP. Information states can be represented by complete historical data or appropriate sufficient statistics. In POMDPs, observations are always associated with states and actions. According to Hauskrecht (1997), there are many different ways to define how this relation occurs:

- POMDP with standard (forward triggered) observations – an observation depends solely on the current process state and the previous action.
- POMDP with backward triggered observations – an action a_t performed at time t causes an observation about the process state s_t to be made. That is, the action performed at time t enables the observation that refers to the "before action" state.
- POMDP with delayed observations – an action issued by an agent at time t will be performed at time $t + k$ and an observation made at time t will become available to the agent at time $t + k$.

In this thesis, we will focus on explore how one can construct appropriate sufficient information states for standard (forward triggered) observations.

2.5 POMDPs as Belief State about MDPs

According to Cassandra (1998a), an information state, b, is simply a probability distribution over the set of states, S, with $b(s)$ being the probability of occupying state s. We define $B = P(S)$ to be the space of all probability distributions over S. A single information state can capture the relevant aspects of the entire previous history of the process, and more importantly can be updated after each state transition to incorporate one additional step into the historical data set.

The information state estimator $\tau : B \; x \; A \; x \; \Omega \rightarrow B$ defines the next belief state, given the previous belief state (b), the previous action (a) and the previous observation (o). If the observations are always caused by the previous action, the current state is b, the previous action is a and the resulting observation is o, then the state estimator can calculate the next belief state b' from the previous state b using Bayes rule. Equation (3) defines $b_a(s')$, the probability of the new state to be s' given the a executed action:

$$b_a(s') = \sum_{s\prime \in S} T(s'|s,a)b(s) \tag{3}$$

Equation (4) describes $b_a(o)$, the probability of the next observation to be o given the a executed action.

$$b_a(o) = \sum_{s\prime \in S} O(o|s',a)b_a(s') \tag{4}$$

The new belief state b' is composed by the probabilities $b'(s')$, according to equation (5):

$$b'(s') = \frac{O(o|s',a)b_a(s')}{b_a(o)} = \frac{O(o|s',a)\sum_{s'\in S} T(s'|s,a)b(s)}{\sum_{s\prime\in S}[O(o|s',a)\sum_{s'\in S} T(s'|s,a)b(s)]} \tag{5}$$

In equations (6) and (7), the function T' gives the probability of the system to pass from a belief state b to another, b', after executing an action a:

$$T'(b'|b,a) = P(b'|b,a) = \sum_{o \in \Theta} P(b'|b,a,o)P(o|b,a) \tag{6}$$

where

$$P(b'|b,a,o) = \{ \begin{matrix} 1 \; if \; \tau(b,a,o) = b' \\ 0, otherwise \end{matrix} \tag{7}$$

The reward function ρ presented in equation (8) is defined for the belief states and gives the expected reward of each action, given the probabilities of the system to be in each state:

$$\rho(b,a) = \sum_{s \in S} b(s)R(s,a) \tag{8}$$

The solution to the MDP of continuous state space (B, A, T', ρ) is the solution to POMDP used to build it (a detailed explanation of this section is in https://dl.dropboxusercontent.com/u/105316427/Reference%20List.docx).

2.6 Policies

Given a tuple (S, A, T, R, Ω, O) specifying a POMDP, what action should an agent execute at each time-step to earn as much reward as possible over time? Let us define $\prod$ to be the set of all policies π (action strategies) that an agent can execute. Roughly speaking, a policy is some strategy that dictates which action α to execute (at each time-step) based on some information previously gathered. The relevant information available to the agent consists of some belief b_0 about the initial state of the world and the history (sequence) of actions and observations experienced up to the current time-step t $(hist_t = (a_0, o_1, a_1, o_2, \ldots, a_{t-1}, o_t))$. Since the agent may not have complete knowledge of the initial state of the world, we use b_0 to denote a probability distribution over all possible states that corresponds to his belief about the initial state. Hence, a policy π is a mapping from initial beliefs and histories to actions (Poupart, 2005).

A policy for a belief POMDP can be viewed as a policy for an information state MDP. The POMDP policy definition above is Markovian regarding the information states but not Markovian regarding the POMDP states as originally described.

2.7 Value Function

Given the set of all policies $\prod$, we need a mechanism to evaluate and compare policies. Roughly speaking, the goal of an agent is to maximize the amount of reward earned over time. This loosely defined criterion can be formalized in many ways: one may wish to maximize total (accumulated) or average reward, expected or worst-case reward, discounted or undiscounted reward. Unless otherwise stated, this thesis assumes an expected total discounted reward criterion, since it is by far the most popular in the literature. Mathematically, we define the value $V^{\pi}(b_0)$ of executing some policy π starting at belief state b_0 to be the expected sum of the discounted rewards earned at each time-step (Poupart, 2005). Equation (9) presents this behavior:

$$V^{\pi}(b_0) = \sum_{t=0}^{h} \gamma^t \sum_{s \in S} b_t(s) R\big(s, \pi(b_t)\big). \qquad (9)$$

Here, $b_t(s)$ denotes the probability of s according to belief state b_t and $\pi(b_t)$ denotes the action prescribed by policy π at belief state b_t.

Using value functions V, we are now in a position to order policies. A decision theoretic agent prefers π to π' when $V^{\pi}(b) \geq V^{\pi'}(b)$ for all belief states b. This preference ordering is a partial order because there are pairs of policies for which neither policy has a value function greater than the other one for all belief states. On the other hand, there always exists an optimal policy π^* such that its value function V^{π^*}dominates all other policies $\big(V^{\pi^*}(b) \geq V^{\pi}(b)\ \forall \pi, b\big)$ (Poupart, 2005). A detailed explanation of this section is in https://dl.dropboxusercontent.com/u/105316427/Reference%20List.docx.

2.8 Representation in Hyperplanes

The representation in hyperplanes as shown in Figure 2 is commonly used in exact algorithms. There is a set of vectors associated with each action, where each vector defines a hyperplane giving the expected reward for taking that action, given the belief state (i.e., there remains a value function). When multiplied by a state of belief b, each vector will give the expected reward as long as the action associated with it is taken and an optimal policy is followed until the last time decision. This hyperplanes set is usually denoted by Γ and Γ_i is the policy of the i^{th} time decision.

Figure 2 shows an example of policy where the belief state is represented as $P(s_0)$ from 0 to 1. Each hyperplane represents the expected value of an action, the stretch where a hyperplane dominates all others is the one where the action represented by it is optimal. In the figure below, the action α_4 is useless because it is dominated by the other. The action represented by the vector α_1 is optimal whenever the belief state have $p(s_0) \geq 0.7$. The action of vector α_2 is optimal when $0.4 \geq p(s_0) \geq 0.7$ and the action of vector α_3 when $p(s_0) \leq 0.4$.

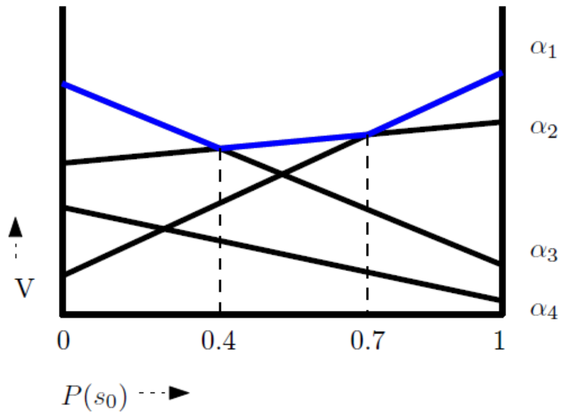

Figure 2: Policy for a POMDP represented as a hyperplane set

Source: Pellegrini and Wainer (2007)

2.9 Solution Algorithms

Over the years, many algorithms have been proposed to find optimal POMDP policies. In the 1960s, the Operations Research community developed the POMDP framework that was first formalized by Drake (1962). Then, in the 1970s, Smallwood and Sondik (1973, 1971) discovered the piecewise-linear and convex properties of optimal value function. This discovery enabled the formulation of several dynamic programming (DP) algorithms.

In this thesis, the POMDP-Solve developed by Cassandra (2015) will be used. According to Cassandra (2015), the pomdp-solve program (written in C language) solves problems that are formulated as POMDPs. It uses the basic dynamic programming approach for all algorithms, solving one stage at a time but working backwards in time. It solves finite horizon problems with or without discounting. It will stop solving if the answer is within a tolerable range of the infinite horizon answer, and there are a couple of different stopping conditions (requires a discount factor less than 1.0). Alternatively, it solves a finite horizon problem for some fixed horizon length. The code actually implements a number of POMDP solution algorithms (Cassandra, 2015):

- Enumeration

The idea is to generate all the possible vectors the computer could build. To build a vector the computer requires selecting an action and a vector in V for each observation. Thus, it must generate a large number of vectors. Many of these are not useful, since they are completely dominated by other vectors over the entire belief space. It is possible to eliminate the useless ones at the expense of some computing time, but regardless, just enumerating the vectors takes a long time even for some small problems.

- Two Pass

This algorithm starts with an arbitrary belief point, builds the vector for that point and then defines a set of constraints over the belief space where this vector is guaranteed to be dominant.

The region defined is actually the intersection of three easier to describe regions. When a vector is built from a belief point b it is known which strategy that vector represents. This strategy is the best one for that belief point and some nearby belief points. However, it might not be the best strategy for all belief points. There are two ways that this strategy might not be the best: either the immediate action does not change and the future strategy changes; or another action might become better.

- Linear Support

Linear support algorithm forgets about focusing on actions and future courses of actions. It simply picks a point, generates the vector for that point and then checks the region of that vectors to see if it is the correct one at all corners of the region. If not, it adds the vector at that point and checks its region.

- Witness

This algorithm defines regions for a vector and looks for a point where that vector is not dominant. Unlike the previous algorithms, it does not worry about all the actions all the time. It concentrates on finding the best value function for each of the actions separately. Once it is found, it will be combined into the final V' value function.

- Incremental Pruning

The incremental pruning algorithm combines elements of Enumeration and Witness algorithms. Like Witness, it considers building sets of vectors for each action individually and then focusing on each observation at a time. The basic idea is to eliminate doing all this region business. Since the main problem is finding all the different combinations of future strategies, it focuses on this specific aspect. Ater that, adding the immediate rewards is an easy step.

Lots of researchers have proposed using UAVs for assistance in Search and Rescue operations. Merino *et al.* (2012) propose a system to use UAVs for forest fire monitoring. Maza *et al.* (2010) have proposed a distributed architecture for disaster management as part of AWARE project. Daniel *et al.* (2011) have discussed the use of UAVs to track the plume clouds.

In the next chapter, some applications of POMDP in UAVs are presented through a systematic literature review, which also considers the use of UAVs in humanitarian relief.

3 Literature Review

This chapter presents the literature review about the use of POMDP technique in drones for rescue operations from three aspects: the applications of UAV's in humanitarian relief, the applications of the POMDP technique in UAVs and the use of simulation processes in humanitarian logistics.

Liu *et al*. (2014) give an overview of the state of UAV developments and their possible applications in civil engineering, like seismic risk assessment, transportation, and disaster response. Roahcs *et al.* (2006) also summarize the civilian application of the UAVs with focusing on their application in emergency management. Ezequiel *et al.* (2014) present various applications of UAV aerial imagery, in the post-disaster assessment and recovery, in the Philippines. Camara (2015) discusses some possible applications of drones over disaster scenarios. Zhang and Wu (2014) study UAVs applications in the field of disaster prevention and mitigation, search and rescue operations, land resources monitoring, and forest fire prevention. Zheng *et al.* (2013) analyze methods of accessing and processing digital image data in mountainous area and its application to emergency response management of geological hazard.

On the previous review papers, the authors did not present the research methodology neither the statistical results about the considered papers. Given the growing trend of works published in this field, it is important to expose the research methodology used in the literature review to allow other authors to update the review in the future. This research presents a systematic literature review about the applications of UAVs in humanitarian relief with the purpose of helping researchers to understand what can still be explored in this area. This section aims to identify trends and suggests directions for future research.

3.1 Defining Humanitarian Logistics

According to the International Federation of the Red Cross and Red Crescent Societies (IFRC), disasters can be defined as sudden, calamitous events which disrupt the activities of a society or a community and cause human, material, economic, or environmental losses that exceed the recovery capacity of the affected community or society using only its own resources (NATARAJARATHINAM *et al.*, 2009).

Van Wassenhove (2006) proposed a classification of natural and man-made disasters according to the speed with which the disaster strikes: slow-onset or sudden-onset. Famine, drought, political, and refugee crises are examples of the former category, whereas the latter includes, for example, earthquakes, hurricanes, technological failures, and terrorist attacks.

There are four primary stages of a disaster: mitigation, preparedness, response, and recovery. Mitigation is assessing possible sources of crisis and identifying sets of activities to reduce and/or eliminate those sources so that crisis never happens or its impact is reduced. Preparedness is developing a crisis response plan and training all the involved parties so that in the case of a crisis people know their roles and will effectively be able to deal with it. Response constitutes the set of immediate actions taken after a crisis occurs, and it aims to reduce the impact by utilizing the plans created during the preparedness stage. Recovery is the final set of activities in which the objective is to support all involved parties until they resume their normal operations (NATARAJARATHINAM *et al.*, 2009).

Humanitarian logistics is the processes and systems involved in mobilizing people, resources, skills and knowledge to help vulnerable people affected by disaster (VAN WASSENHOVE, 2006).

3.2 Research Methodology

The research methodology adopted in this research consists of three steps:

1. Select databases: Scopus, Web of Science, ProQuest, Scielo International, Emerald and Science Direct;
2. Filter the databases with the following terms in their topic, title, abstract or keywords.

   a) "UAV OR Drone" and "Humanitarian OR Disaster OR Relief OR Emergency OR Crisis" (in section 3.2.1). There are others synonyms for UAVs but they were not considered due to the fact that the only

6 papers found with these keywords were not relevant. Time restriction filters were not used;

b) "Humanitarian Logistics" AND "Simulat*" (in section 3.2.2);
c) "UAV OR Drone" AND "POMDP OR Partially Observable Markov Decision Process" (in section 3.2.3).

3. Read the abstract to confirm the relevance of the papers.

3.3 Results

3.3.1 Applications of UAVs in Humanitarian Relief

After applying the methodology above, 117 relevant papers were found (see https://dl.dropboxusercontent.com/u/105316427/Reference%20List.docx for the complete reference list). Conference proceedings address 77% of the relevant papers and journals represent 23% of them. The 26 papers from journals were published each one in a different journal.

In addition to the filters mentioned in section 3.2, the articles in this section were classified as follows:

- Type of disaster (VAN WASSENHOVE, 2006);
- Phase of the disaster in which the application of UAV was used (NATARAJARATHINAM *et al*., 2009);
- Year of publication;
- Approach – it can be a theorical application or a practical case study;
- Purpose of the applications:
    - 3D Mapping;
    - Mapping of Affected Areas;
    - Image Analysis;
    - UAV's Network;
    - UAV's with Sensor in Detection Operations;
    - Cooperation between UAV's and others vehicles;
    - Review Papers;
    - Route Planning Algorithm;
    - Optimization Problem;
    - Security;

- Medical Surgery.

The categorization approach, year of publication and purpose are suggested by the author of this thesis. The purpose categorization was created based on the author's experience over the reading of the relevant papers and each paper was categorized in only one type of purpose. There are 29 papers that were classified just by their abstract because they were not available.

With the categorizations proposed, some statistic information about the application of UAVs in humanitarian relief is presented.

Type of disaster

Table 1 shows the papers categorized by origin and speed of disaster.

Table 1: Papers categorized by origin and speed of disaster

	Sudden-onset	Slow-onset	ND	Total
Natural	62	0	8	**70**
Man-made	3	5	1	**9**
ND	18	0	20	**38**
Total	**83**	**5**	**29**	

Source: Author

Only 4,3% of the papers address slow-onset disasters, where the use of UAV’s occurs mostly in the military context, such as demining of battlefields (Kruijff *et al.*, 2013). 7,7% of the papers address man-made disasters, such as hazardous chemicals (Wang *et al.*, 2013), atmospheric environmental emergency (Xie *et al.*, 2013) and battlefield’s demining (Moussally and Breiter, 2004). The natural sudden-onset disasters account for 53% of the papers, where the use of UAV’s consists mostly in the mapping of affected areas. 40% of the papers were not classified (ND), in both classes (origin and speed). 10% are review papers.

Phase of disaster

Figure 3 shows the papers categorized by phase of disaster. There were some papers where UAV application occurs in the response and/or recovery phases.

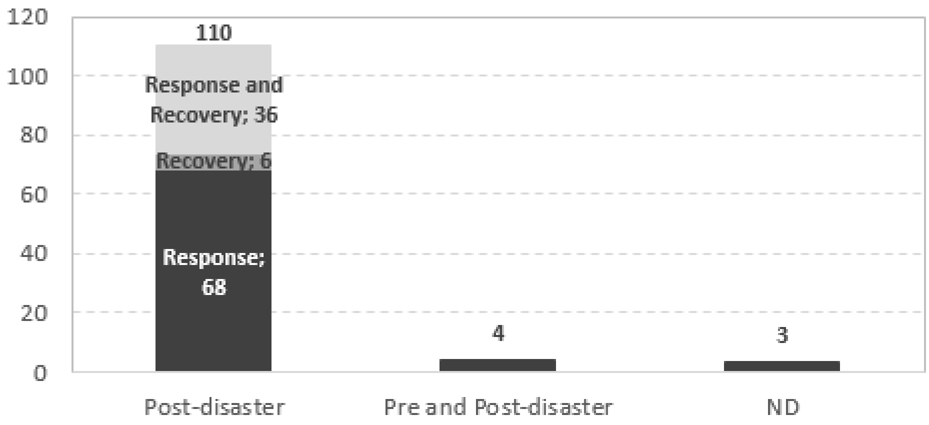

Figure 3: Papers categorized by phase of disaster

Source: Author

Four papers consider pre and post disaster phase and 3 papers are Not Defined. Figure 3 shows that 94% of papers focused on post disaster phase. It can be concluded that research on the post-disaster stages, such as response and recovery, is more widespread than research on the pre-disaster stages, such as mitigation and preparedness. As the number of disaster is still increasing, it indicates that there is a need for research on UAV applications on the pre-disaster phases.

Year of publications

It is important to reinforce that 73% of the papers were written after 2009 (last 5 years), as presented in Figure 4, which means that the literature review reflects recent applications of UAVs.

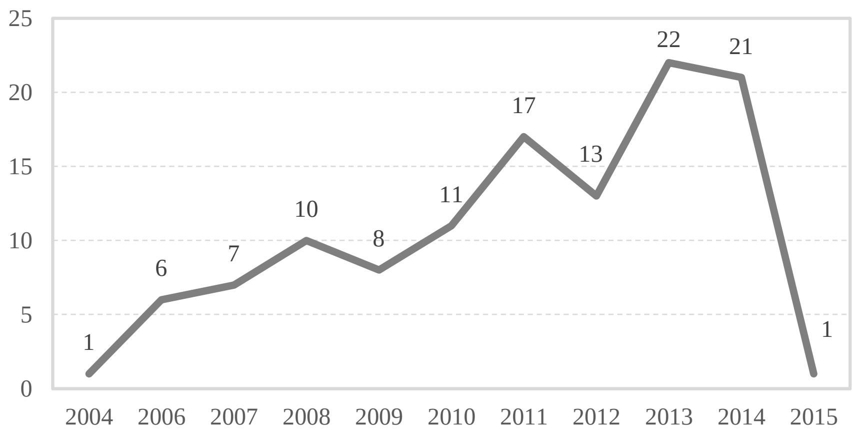

Figure 4: Papers categorized by year of publication

Source: Author

Approach

In the Figure 5, it is possible to see that 65% of the papers showed a case study, which means that UAV's were actually used to validate the methodologies, algorithms and models proposed. This finding represent that UAV use in humanitarian logistics can already be seen as a highly feasible possibility, besides being an efficient and effective implementation.

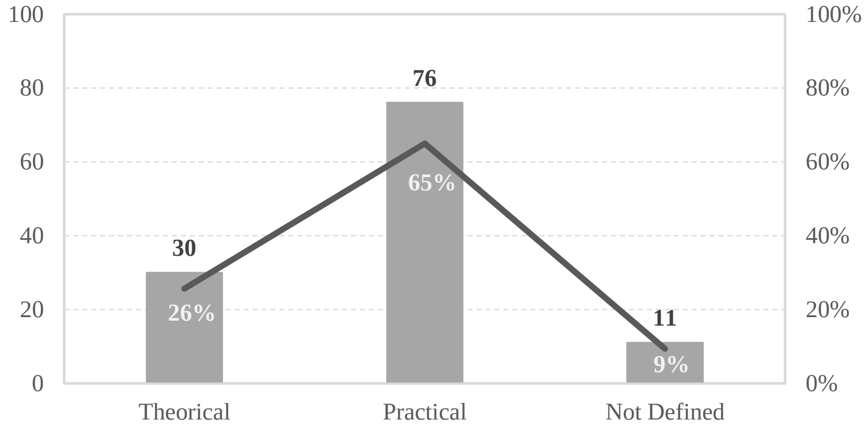

Figure 5: Papers categorized by approach

Source: Author

Purpose of the applications

Figure 6 shows the papers categorized by the purpose of the application.

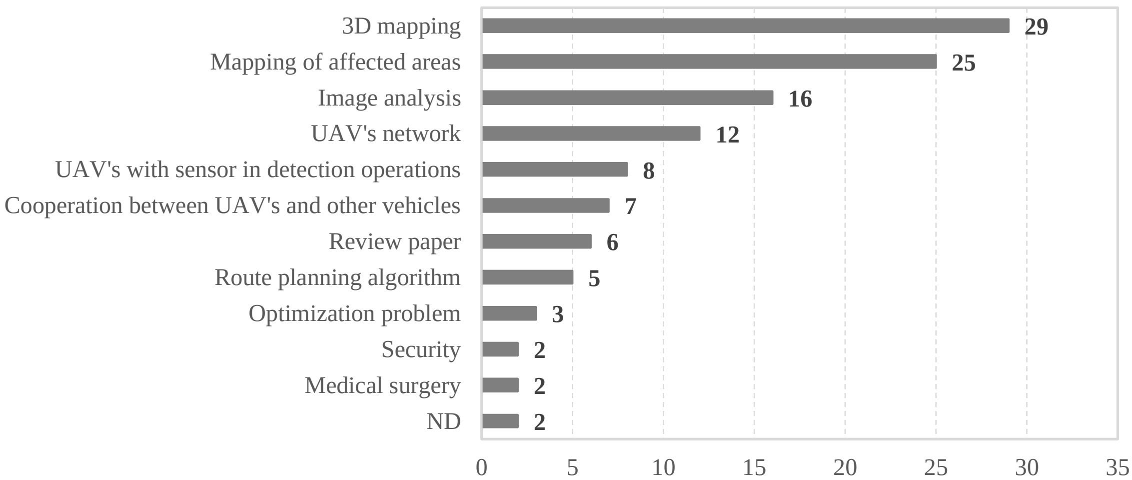

Figure 6: Papers categorized by purpose of the application

Source: Author

From Figure 6, it can be concluded that 60% of the papers address the first three classes: 3D mapping, mapping of affected areas and image analysis, which are very related topics. This relation occurs because the main objective of early impact analysis after a disaster is to define the damages of infrastructure, facilities and human life/health/integrity, and that requires suitable data, such as high-resolution satellite images. The 3D mapping and the image analysis provide more clear views of the affected areas as input data for early impact analysis in medium and large-scale map.

Nex and Remondino (2014) report the state of the art of UAV for geomatics applications (3D mapping), giving an overview of different UAV platforms, applications, and case studies, showing also the latest developments of UAV image processing.

Tsai *et al.* (2011) use the 3D mapping technique to collect spatial information for disaster assessment after devastating Typhoon Morakot that hardly hit southern Taiwan during summer 2009.

Xu *et al.* (2014) present an example of UAS developed for rapidly obtaining disaster information mapping affected areas. Tests showed that the system plays an important role in the work of investigating and gathering information about disaster in epicentral areas of the Lushan Earthquake, Sichuan, China, such as road detection, secondary disaster investigation, and rapid disaster evaluation.

Tatham (2009) use a case study of the 2005 Pakistan earthquake to illustrate how a UAV might be employed and its potential effectiveness.

Patterson *et al.* (2014) present novel work on autonomously identifying Safe Landing Zones (SLZs) through image analysis which can be utilized upon occurrence of a safety critical event.

Gong *et al.* (2010), taking Beichuan as the study area, construct the hierarchical stripping classification (HSC) framework, a human-computer interactive interpretation framework, to detect the geological hazards produced by the Wenchuan earthquake. Change detection was performed by overlaying the classification maps before and after the earthquake.

Ueyama *et al.* (2014) outline a solution that employ UAVs to reduce the problems arising from faults in a sensor network when monitoring natural disasters like floods and landslides. In the solution put forward, UAVs can be transported to the site of the disaster to mitigate problems caused by faults (e.g., by serving as routers or even acting as a data mule). Experiments conducted with real UAVs and with our WSN-based prototype for flood detection (already deployed in São Carlos, State of São Paulo, Brazil) have proven that this is a viable approach.

Delle Fave *et al.* (2012) present a case study whereby the max-sum algorithm is applied to coordinate a team of UAVs to provide live aerial imagery to the first responders operating in the area of a disaster.

Regarding UAV's with sensor in detection operations, Xie *et al.* (2013) present a design framework of the UAV platform based atmospheric environmental emergency monitoring system with regard to the components, functions and procedures. The application of UAV's in atmospheric environment emergency monitoring system has been one of the important future developmental directions.

Towler *et al.* (2012) developed a remote sensing system for radiation detection and aerial imaging using a 90 kg autonomous helicopter and sensing payloads for the radiation detection and imaging operations.

Lindemuth *et al.* (2011) describe a novel marsupial (one robot deploys another robot) unmanned surface-aerial team for littoral environments as an alternative to a solo UAV or unmanned underwater vehicle (UUV). By itself, a UAV can provide above the waterline sensing but cannot provide details below the surface.

Artemenko *et al.* (2014) develop an UAV that moves around buildings and localizes "survived" devices inside a building. This can help to detect victims and to accelerate the rescue process – in which fast and accurate localization is essential. A LMAT (Localization algorithm with a Mobile Anchor node based on Trilateration) path planning algorithm is being validated using simulations and evaluated in experiments using a real UAV.

When a disaster occurs, the UAV of each household should work collaboratively in order to collect information in an efficient manner. To achieve the purpose, UAVs may exchange information through intermittently connected mobile ad hoc networks. Nishikawa *et al.* (2014) propose a planning-based routing protocol for area sensing. The proposed protocol exploits planned route of each node to collect information efficiently.

Quaritsch *et al.* (2010) deploy an aerial sensor network with small-scale, battery-powered and wirelessly connected UAVs carrying cameras for disaster management applications. The UAVs fly in formations and cooperate to achieve a certain mission. This paper focus on the optimal placement of sensors formulating the coverage problem as integer linear program (ILP).

Murtaza *et al.* (2013) solve the coverage problem while optimizing the time to find victim when number of victims in the disaster area is unknown. The authors formulate the path-planning problem for aerial wireless sensor networks involved in search and rescue operation as a constrained coverage problem. The constraint is based on the idea of assigning higher priorities to the areas, which are more probable to contain victims.

UAVs must be reliable and have the ability to take appropriate action when some functionality is lost due to failure. Fast system reliability assessment techniques such as the Binary Decision Diagram (BDD) technique can be used as part of the decision making process to decide when the likelihood of the autonomous vehicle successfully performing its intended task becomes unacceptably low and what action needs to be taken to mitigate this situation. Brazenaite *et al*. (2010) present a reconfiguration process, which is based on optimizing the mission reliability under its current conditions and environment. This is demonstrated using a UAV carrying out a search and rescue operation.

Harnett *et al.* (2008) demonstrate an experimental surgical robot using an UAV as a network topology. For the first time, a mobile surgical robotic system was deployed to an austere environment and surgeons were able to remotely operate the systems wirelessly using a UAV. The network topology demonstrated a highly portable, quickly deployable, bandwidth-sufficient and low latency wireless network required for battlefield use.

Lum *et al.* (2007) present an experiment in the area of Mobile Robotic Telesurgery (MRT). The experiment demonstrated that under minimal or low visual feedback and network time delay, surgeons are still able to perform surgical tasks.

Discussion

The applications discussed in this paper have shown that UAV aerial imagery provides domain experts and decision makers essential data for analysis and effective action.

Earth observation can significantly contribute to improving efforts in developing proper disaster mitigation strategies, and providing relevant agencies with very important information for alleviating impacts of a disaster and relief management. However, technical and financial issues have challenged the traditional use of satellite and aerial images for this task (TATHAM, 2009).

According to Meier (2014), very small and lightweight UAVs are already being used in disaster response, currently to capture high-resolution imagery, but soon for micro-transportation too. Google has already built and tested autonomous aerial vehicles, and believes they could be used for goods deliveries. They could be used after earthquakes, floods, or extreme weather events, the company suggested, to take small items such as medicines or batteries to people in areas that conventional vehicles cannot reach (STEWART, 2014).

In the military context, armed UAVs pose ethical issues not only with respect to their use in armed conflict, but also concerning the prevention of war. In order to prevent dangers for arms control, international humanitarian law, for military stability as well as for society, armed UAVs should be limited (ALTMANN, 2013).

From a social acceptance perspective, it is extremely important that concerns of privacy are addressed appropriately. Public concerns of insufficient safeguards to ensure that UAVs are not used to spy on citizens and unduly infringe upon their fundamental privacy, need to be thoughtfully addressed before allowing UAVs to fly in the national airspace. The guiding principles for Federal Aviation Administration (FAA) policies include mainly the safety of people in the air and on the ground (NAMADURI *et al.*, 2013).

Another challenge that needs to be considered, for practical applications, is related to the access of airspace. According to Namuduri *et al.* (2013), after Hurricane Katrina, Joint Terminal Air Controller (JTAC), located in New Orleans, deployed their Evolution Tactical UAVs. Their attempts to use these UAVs were restricted due to FAA regulations on accessing airspace. The workaround was to attach small Evolution UAV to the bottom of a UH-60 helicopter. In response to the growing demand for civilian use of UAVs, FAA has been rigorously pursuing policies for safe and secure use of UAVs in the national airspace.

Given that the cost of building and operating a UAVs is reducing whilst its operational capabilities are increasing, it would seem likely (if not inevitable) that UAVs would perform an useful and cost-effective function within the overall post-disaster needs assessment process and, thereby, assist in the mitigation of the risk in the response to such disasters (TATHAM, 2009).

Innovations in UAVs become valuable tools in capturing and assessing the extents and amount of damages (XU *et al.*, 2014). Their UAS is becoming increasingly popular for civilian use due to their relatively low cost, ease of operation and the emergence of low cost navigation and imaging sensors, with performances comparable to higher priced sensors. The operational nature and cost factors make this technology applicable to build a low cost mapping system (TATHAM, 2009).

This increasing use of UAVs for humanitarian purposes explains why the United Nations (UN) recently published an official policy brief on the topic. A number of UN groups like the Office for the Coordination of Humanitarian Affairs (OCHA) are actively exploring the use of UAVs for disaster response. These organizations have also joined the Humanitarian UAV Network (UAViators, 2014) to promote the safe and responsible use of UAVs in humanitarian settings (MEIER, 2014).

3.3.2 Simulation process in humanitarian logistics

Simulation processes are frequently used in the validation of optimization models. In humanitarian logistics, these models aim to minimize the transportation costs or the time to deliver the supplies.

Diaz *et al.* (2013) present an overview of some of the most relevant modeling efforts discussed in the literature. They also present opportunities for the application of modeling and simulation (M&S) in specific areas of humanitarian logistics and emergency management.

Camacho-Vallejo *et al.* (2014) validate a model for humanitarian logistics to optimize decisions related to the distribution of international aid after a catastrophic disaster. Their case study address the earthquake in Chile in 2010.

Mulyono and Ishida (2014) simulate a volcanic eruption disaster to validate their method of improving the performance of lateral transshipment operations through cluster formation of shelters before the disaster event occurs.

Gibbons and Samaddar (2009) use fully factorial computer simulation to identify referral network attributes and referral decision rules that streamline the routing of people to urgent, limited services. As an example of a scenario, the model represents vaccine delivery in a city of 100.000 people during the first 30 days of a pandemic.

Mohan *et al.* (2013) present a detailed simulation model of the warehouse operations where food is processed which serve as a framework for making changes that improve the efficiency of the operations in terms of handling extra volume without investing in additional warehouse space.

Altay and Pal (2014) use agent-based modeling and simulations to show that clusters, if properly utilized, encourage better information flow and thus facilitate effective response to disasters.

Lau *et al.* (2012) analyze the simulation results to evaluate the performance of an optimization model for post-disaster response. Their model aims to automate the coordination of scarces resources that minimizes the loss of human lives.

Ertem *et al.* (2012) use a genetic algorithm, a simulated annealing algorithm and an integer program to analyze the bid construction phase of procurement actions in disaster relief and humanitarian logistics.

Uchida (2012) proposes a model that clarifies how disaster warning issuance conditions affect “cry wolf” syndrome and develops a simulation model that expresses the behavior of local authority and the residents.

3.3.3 Applications of POMDP technique in UAVs

The Partially Observable Markov Decision Process (POMDP) model is usually explored for high level decision making for Unmanned Air Vehicles (UAVs) because of its imperfect sensors and uncertainties due to the stochastic nature of the problem.

Ragi and Chong (2012, 2013a) present a path-planning algorithm to guide unmanned aerial vehicles for tracking multiple ground targets based on the theory of POMDP. More recently, Ragi and Chong (2013b, 2014), design a decentralized guidance control method for autonomous UAVs tracking multiple targets. They incorporate the cost of communication into the objective function of the POMDP, i.e., they explicitly optimize the communication among the UAVs at the network level along with the kinematic control commands for the UAVs.

Chanel *et al.* (2012, 2013) present a case study about the multi-target detection and recognition mission by autonomous UAV. The POMDP model deals in a single framework with both perception actions (controlling the camera's view angle), and mission actions (moving between zones and flight levels, landing) needed to achieve the goal of the mission, i.e., landing in a zone containing a car whose model is recognized as a desired target model with sufficient belief.

An application of UAVs of military importance is that of using a team of UAVs carrying passive sensors to detect and track enemy emitters, e.g., radars. Sarunic (2009a, 2009b) present an algorithm for trajectory optimization of autonomous aerial vehicle performing multiple target tracking. The problem is approached by formulating it as a POMDP and developing a moving-horizon solution taking into account short and long term costs.

Miller *et al.* (2009a, 2009b) describes a principle framework for designing a planning and coordination algorithm to control a fleet of UAVs for the purpose of tracking ground targets. The algorithm runs on a central fusion node that collects measurements generated by sensors on-board the UAVs, constructs tracks from those measurements, plans the future motion of the UAVs to maximize tracking performance, and sends motion commands back to the UAVs based on the plan.

Hanselmann *et al.* (2008) propose an algorithm for scheduling and control of passive sensors. This algorithm is based on a POMDP and an expected short or long-term reward given by the sum of Rényi information divergences between Gaussian densities. This approach allows effective and efficient implementations and the algorithm is demonstrated on simulations of situation scenarios of practical interest.

Nowak and Lamont (2008) present an innovative new paradigm for developing SO-based (Self-Organized-based) autonomous vehicles providing a structured approach to organizing a Self-Organized (SO) development technique that can be crossed utilized in multiple disciplines.

Balaban and Alonso (2013) describe a general modeling approach for a class of prognostic decision making (PDM) problems with non-linear system degradation processes and uncertainties in state estimation, action effects, and future operating conditions. The approach is based on continuous POMDP used in conjunction with "black box" system simulations. The approach is illustrated with a mission planning case study where a PDM system is tasked with optimizing the vehicle route after an in-flight component fault is detected.

Schesvold *et al.* (2003) present two models in their paper: one uses planning horizon to model the fuel level, while the other models the fuel level explicitly in the states.

3.3.4 Conclusion

This chapter presented a systematic literature review about the applications of UAVs in humanitarian relief and showed an increase in the number of publications on the subject over the past ten years. Although humanitarian relief is a recent and growing area, it should be noted that only one author of this area is studying the use of drones in emergency situations (Tatham, 2009). The most part of contributions in this area, which comes from robotic and mechanical engineering, are focused on improving the equipment's performance. In section 3.3.1, 117 papers were surveyed, classified, and some gaps were identified, allowing suggestions for future research. The conclusions are the need for more studies about mitigation and preparedness and the small number of papers on man-made and slow-onset disasters. It should be noted that UAV is a promising technology, which continues to be technically developed, that have positive impact in humanitarian settings and is already being used by universities and private organizations, such as Google, to test and improve their methodologies, algorithms and models.

This chapter has also showed that the use of the POMDP technique applied to drones involves optimization of the communication among UAVs, multi-target detection and recognition, and SO-based (Self-Organized-based) autonomous vehicles. Simulation applications in Humanitarian Logistics has the bias to test the models and algorithms developed. Although these solutions are used in very specific ways, they together have a potential application for humanitarian relief. In the next chapter, a methodology is proposed where UAVs cover the disaster affected area based on partial knowledge of the terrain before hand. This methodology prioritises the cell according to their location and proposes a solution to this constrained coverage problem based on POMDP.

4 Methodology

This chapter presents a methodology to model the constrained coverage problem, solve it based on the POMDP technique and test it through simulation process. This methodology consists of four steps: modeling, simulating, solving, and analyzing statistics. The flowchart resuming these processes is presented in Figure 7.

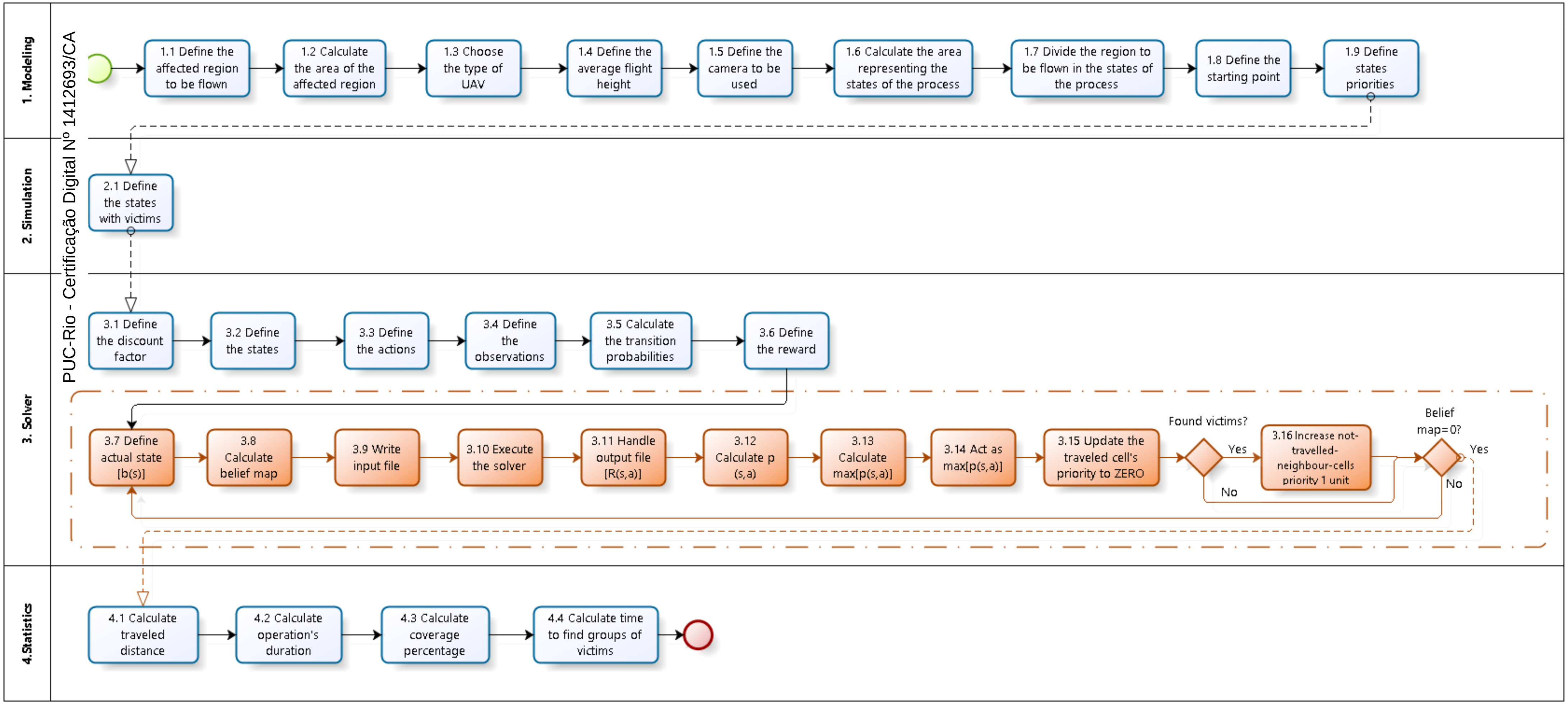

Figure 7: Methodology's Flowchart

Source: Author

4.1 Modeling

1. **Define the affected region to be flown**

   It should be defined by a specialist who can identify which are the most affected areas.

2. **Calculate the area of the affected region**

   In this thesis, Daftlogic (2015) will be used to calculate the area of the affected region, but any tool that can find the distance between two or more points on a map can be used.

3. **Choose the type of UAV**

   The type of UAV depends on the take off weight, flight altitude, flight time (endurance), flight distance (data link range) and type of mission. Bento (2008) classified the types of UAVs according to Table 2.

Table 2: Classification of types of UAVs

	Category (acronym)	Maximum Take Off Weight (kg)	Maximum Flight Altitude (m)	Endurance (hours)	Data Link Range (Km)	Example	
						Missions	Systems
Micro/Mini UAVs	Micro (MAV)	0.10	250	1	< 10	Scouting, NBC sampling, surveillance inside buildings	Black Widow, MicroStar, Microbat, FanCopter, QuattroCopter, Mos-quito, Homet, Mite
	Mini	< 30	150-300	< 2	< 10	Film and broadcast industries, agriculture, pollution measurements, surveillance inside buildings, communica-tions relay and EW	Mikado, Aladin, Tracker, DragonEye, Raven, Pointer II, Carolo C40/P50, Skorpio, R-Max and R-50, Robo-Copter, YH-300SL
Tactical UAVs	Close Range (CR)	150	3.000	2-4	10-30	RSTA, mine detection, search & rescue, EW	Observer I, Phantom, Copter 4, Mikado, RoboCopter 300, Pointer, Camcopter, Aerial and Agricultural RMax
	Short Range (SR)	200	3.000	3-6	30-70	BDA, RSTA, EW, mine detec-tion	Scorpi 6/30, Luna, SilverFox, EyeView, Firebird, R-Max Agri/ Photo, Hornet, Raven, phantom, GoldenEye 100, Flyrt, Neptune
	Medium Range (MR)	150-500	3.000-5.000	6-10	70-200	BDA, RSTA, EW, mine detec-tion, NBC sampling	Hunter B, Mücke, Aerostar, Sniper, Falco, Armor X7, Smart UAV, UCAR, Eagle Eye+, Alice, Extender, Shadow 200/400
	Long Range (LR)	-	5.000	6-13	200-500	RSTA, BDA, communications relay	Hunter, Vigilante 502
	Endurance (EN)	500-1.500	5.000-8.000	12-24	> 500	BDA, RSTA, EW, communica-tions relay, NBC sampling	Aerosonde, Vulture II Exp, Shadow 600, Searcher II, Hermes 450S/450T/700
	Medium Altitude, Long Endurance (MALE)	1.000-1.500	5.000-8.000	24-48	> 500	BDA, RSTA, EW weapons delivery, communications relay, NBC sampling	Skyforce, Hermes 1500, Heron TP, MQ-1 Predator, Predator-IT, Eagle-1/2, Darkstar, E-Hunter, Dominator
Strategic UAVs	High Altitude, Long Endurance (HALE)	2.500-12.500	15.000-20.000	24-48	> 2.000	BDA, RSTA, EW, communica-tions relay, boost phase intercept launch vehicle, airport security	Global Hawk, Raptor, Condor, Theseus, Helios, Predator B/C, Libellule, EuroHawk, Mercator, SensorCraft, Global Observer, Pathfinder Plus,
Special Task UAVs	Lethal (LET)	250	3.000-4.000	3-4	300	Anti-radar, anti-ship, anti-aircraft, anti-infrastructure	MALI, Harpy, Lark, Marula
	Decoys (DEC)	250	50-5.000	< 4	0-500	Aerial and naval deception	Flyrt, MALD, Nulka, ITALD, Chukar
	Stratospheric (Strato)	TBD	20.000-30.000	> 48	> 2.000	-	Pegasus
	Exo-strato-spheric (EXO)	TBD	> 30.000	TBD	TBD	-	MarsFlyer, MAC-1

Source: Adapted from "UVS-International-"UAV System producers & Models: All UAV Systems Referenced," 2006

TABLE 1. UAV Classification

Source: Bento (2008)

4. **Define the average flight height**

   The average flight height depends on the type of UAV, which was already defined in the last step of the process. For example, a special task UAV can fly above 30.000 meters.

5. **Define the camera to be used**

   The camera should have a High Definition (HD) to capture images with sufficient resolution to identify affected people.

6. **Calculate the area representing the states of the process**

   The size of each state, e^2 square meters, as shown in Figure 8, should represent the area from which the UAV can capture images with sufficient resolution to identify affected people. This area depends on the camera resolution and the flight altitude, which were already defined in the last steps. Let h be the flight height, α the camera angle and e^2 the area representing the states of the process. e can be calculated according to equation (10):

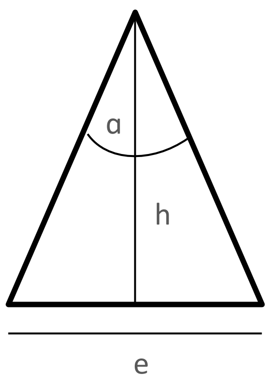

Figure 8: Area representing the states of the process

Source: Author

$$e = 2 * h * \tan\left(\frac{\alpha}{2}\right) \qquad (10)$$

7. **Divide the region to be flown in the states of the process**

   The affected area will be visualized as a 2D grid, denoted by A. The grid is divided into square cells, with e^2 square meters, denoted by $a_{ij}$where i and j refer to the x and y axis of the grid.

All the disaster victims to be rescued, referred as X, reside within A. The individual victims are referred as x_i and a cell a_{ij} can have more than one victim.

Some part of the area of interest might be unobservable due to obstacles. For the purpose of this research, it is assumed that these obstacles can be viewed as individual cells. The set of cells containing obstacles are referred to as C. In this thesis, it is assumed that there are no victims located in the cells with obstacles.

8. **Define the starting point**

   The starting point should be an open area so the UAV can take off safely.

9. **Define states priorities**

   Firstly, a criteria should be adopted to prioritise the states of the process. It can be from 0 to 10, for example, where 0 is the state with less probability of having affected people and 10 is the state with more probability. After that, each state should be classified according to this criteria. For the states with obstacles, a priority -1 is used to discourage the drone to go there. It is also used to delimitate the area to be flown.

4.2 Simulating

1. **Define the states with victims**

   The reason to define some states with victims is to test the solver in terms of time to find victims, distance travelled and coverage percentage. In each cell it is possible to find multiple victims.

4.3 Solving

1. **Define the discount factor**

   The discount factor depends on the horizon of the POMDP. In this thesis, infinite horizon POMDPs are assumed with a discount factor strictly less than 1.

2. **Define the states**

   The definition of states is a number indicating each state, from 0 to n, or a list of strings, from a to z, for example.

3. **Define the actions**

The definition of actions can be also a number indicating the actions or a list of strings, one for each entry. These mnemonics strings can not begin with a digit.

4. **Define the observations**

The definition of observations follows the same rule as definition of states and actions, they can be either numbers or strings.

5. **Calculate the transition probabilities**

The transition probabilities depend on the start state, the final state and the actions. They can be represented as the example below:

If the UAV is in the state $s0$ and takes the action A, it will be on the state $s1$ with 100% (or 1.0) of probability. So T: $s1$: $s0$: A 1.0 (see appendix I).

The purpose of these probabilities is to define to which state the UAV can move.

6. **Define the reward**

The reward (or cost) should be defined according to each observation and should represent the benefits of finding victims.

7. **Define actual state $\boldsymbol{b(s)}$**

The specification of the actual state is optional. There are many different formats for the actual state (starting state) in Appendix I.

8. **Calculate belief map**

The initial belief map is defined as B. Belief b_{ij} is the belief for victim being in cell a_{ij} and is a probability between 0 and 1. The initial belief map is defined based on the terrain information.

Once a priority was assigned to each cell, these priorities can be converted into probabilities for initializing the belief map, simply dividing the priority of each cell by the sum of priorities of all the cells. The result becomes the initial belief map for the proposed heuristic.

9. **Write the input file**

The input file should contain the discount factor, states, actions, observations, transition probabilities, actual state (starting state), the belief map (represented as the observation probabilities) and the rewards. The input file format is presented in Appendix I.

10. **Execute the solver**

The step-by-step to execute the solver is described in the POMDP ORG (Cassandra, 2015).

In this thesis only 1 UAV with WiFi connection will be used, which means that in each iteration the solver should be executed only once.

11. **Handle output file $\boldsymbol{R(s,a)}$**

The solver output, which is presented in Appendix II, is a set of vectors $R(s,a)$ which need to be handled (in Excel, for example, change points to commas). These vectors represent the reward for executing the action a if the UAV is in the state s.

12. **Calculate $\boldsymbol{p(s,a)}$**

We should calculate $p(s,a)$ multiplying $R(s,a)$ and $b(s)$ vectors. The $p(s,a)$ vector also represents the reward for executing the action a if the UAV is in the state s, however it considers the probability of the UAV be in the state s.

13. **Calculate max $\boldsymbol{p(s,a)}$**

We can calculate max $p(s,a)$ with Excel functions.

14. **Act as max $\boldsymbol{p(s,a)}$**

Execute the a action associated with max $p(s,a)$. If max $p(s,a) = 0$ it means that the neighbour cells have already been visited so the UAV should go, through a straight line, to the highest priority state (not traveled), starting with the closest ones. There is no need to go to states which $b_{ij} = 0$.

15. **Update the traveled cell's priority to ZERO**

The reason to update the traveled cell's priority to zero is to discourage the UAV to travel there again.

16. **If the UAV found victims, increase not-traveled-neighbour-cells priority 1 unit until the sum of belief map be ZERO.**

The dotted orange line in Figure 7 represents the algorithm below (steps 3.7 to 3.16):

Begin

While $\sum b_{ij} \neq 0$

Ask the solver for an action a

If ρ(s, a_i) = 0, for every i = 0, 1, 2, …, 7

Go, through a straight line, to the highest priority state (not traveled), starting with the closest ones.

If not

Go to the *s'* state which corresponds to the a action

End

4.4 Analyzing Statistics

The analysis of coverage percentage and the time to find groups of victims are proposed in Murtaza *et al.* (2013) to show that POMDP can achieve 100% coverage and can locate victims very fast. In this dissertation, the states have the same area, so the coverage percentage by iteration would be a linear curve. In this thesis, the coverage percentage was calculated based on the total traveled distance instead of the total area.

The traveled distance and operation's duration statistics are also calculated to show that search and rescue operations with drones are viable in terms of mechanic specification.

1. **Calculate traveled distance**

   The traveled distance can be calculated according to the actions, for example, if the UAV can go to only 4 directions (north, south, east, west), the traveled distance in each iteration will be x, but if the UAV can go to 8 directions (including north-east, north-west, south-east, south-west), the traveled distance can be x or $x\sqrt{2}$.

2. **Calculate operation's duration**

   As the traveled distance is already known, the operation's duration can be calculated by dividing the traveled distance by the average speed of the drone.

3. **Calculate coverage percentage**

   The coverage percentage can be calculated, in each iteration, by summarizing the accumulated traveled distance and dividing it by the total traveled distance. Equation (11) describes d_i as the traveled distance in iteration i, D as total traveled distance and the coverage percentage in iteration n can be calculated as:

$$coverage\ \%_n = \frac{\sum_{i=0}^{n} d_i}{D} \tag{11}$$

4. **Calculate time to find groups of victims**

   The time to find groups of victims can be calculated dividing the traveled distance to find groups of victims G_i by the average speed of the UAV. For example, if the UAV traveled 150m until finding the first group of victims and the UAV average speed is 15 m/s, the time to find the first group of victims is 10 seconds.

These statistics are used to measure the POMDP performance but they can also be used to compare the POMDP with the greedy algorithm. According to Roughgarden *et al.* (2013), greedy algorithms are often used to solve optimization problems: you want to maximize or minimize some quantity subject to a set of constraints.

According to Cormen *et al.* (2001), a greedy algorithm always makes the choice that looks best at the moment, based on the greed. That is, it makes a locally optimal choice in the hope that this choice will lead to a globally optimal solution.

If a u_i is in cell a_{ij}, it selects the neighbouring cell a_{kl} based on the greed to find the victim. This leads the u_i to move to a cell with highest belief probability. If there is a set of neighbours N_{ij} which have same belief to have the victim, the UAV choose one cell among N_{ij} at random (Murtaza *et al.*, 2013).

5 Examples

This chapter applies the methodology proposed in Chapter 4 in two illustrative examples, a tornado in Brasil and a refugee's camp in South Sudan, and compares the results with a greedy algorithm.

5.1 Tornado in Xanxerê, Santa Catarina, Brazil

A tornado hit Xanxerê in Brazil's southern Santa Catarina province on April 21st, 2015. Dozens of houses had roofs torn off by the wind, which may have reached 330 km/h, according to the National Institute of Meteorology (Inmet). In the city, two people were killed and about 120 people were taken to hospitals, according to the military police. About 2600 homes were affected according to the balance sheet of the military police, and about a thousand people were left homeless. The electric central of Santa Catarina (Celesc) reported that 200,000 consumer units were left without light in 20 cities in the region, after 11 transmission towers fell or became inclined.

The main affected neighbours were: Pinheiros, Primo Tacca, Bortolon, Esportes, São Jorge and Colatto. See Figure 9.

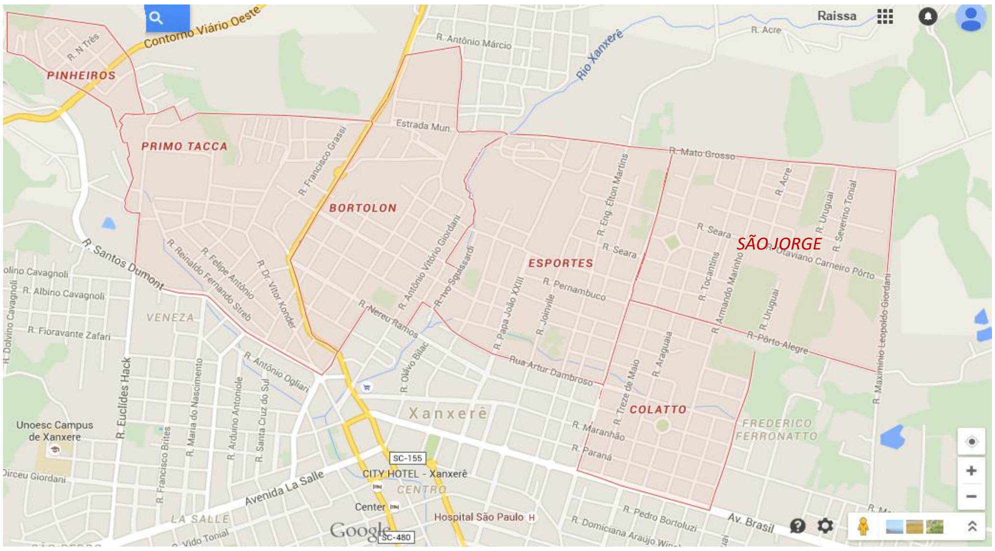

Figure 9: Xanxerê Neighbours

Source: Adapted from Google Maps (2015)

Once the disaster was geographicaly defined, the methodology proposed in chapter 4 will be applied in order to create the drone path planning.

Modeling

1. **Define the affected area to be flown**

   Esportes – the most affected area in Xanxerê, Santa Catarina.

2. **Calculate the area of affected region**

   To calculate the area of Esportes the Daftlogic (2015) was used, which resulted an area of 843.379,38 m² or 0,84 km². See Figure 10.

Figure 10: Esportes Area

Source: Adapted from Daftlogic (2015)

Accordingly to Bento (2008), tactical UAVs are recommended for search and rescue operations. However the mini/micro UAVs will be used because it has a sufficient data link range for Esportes and it has a lower operation cost.

4. **Define the average flight height**

   This example will work with an average flight height of 250m.

5. **Define the camera to be used**

   In this example, a Nikon D7000 camera was considered.

6. **Calculate the area representing the states of the process**

   As the average flight height is 250m and a Nikon D7000 is the camera - it has a 36,8º angle – we can calculate the area from which the UAV can capture images with sufficient resolution to identify affected people. See Figure 11.

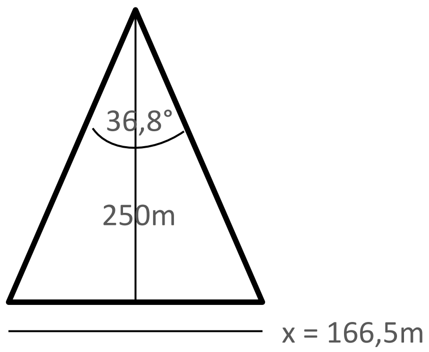

Figure 11: Nikon D7000 Image Resolution

Source: Author

To be conservative, it will be used an area of 150m x 150m instead of 166,5m x 166,5m. Then, the area representing each state is 22.500m².

7. Divide the region to be flown in the states of the process

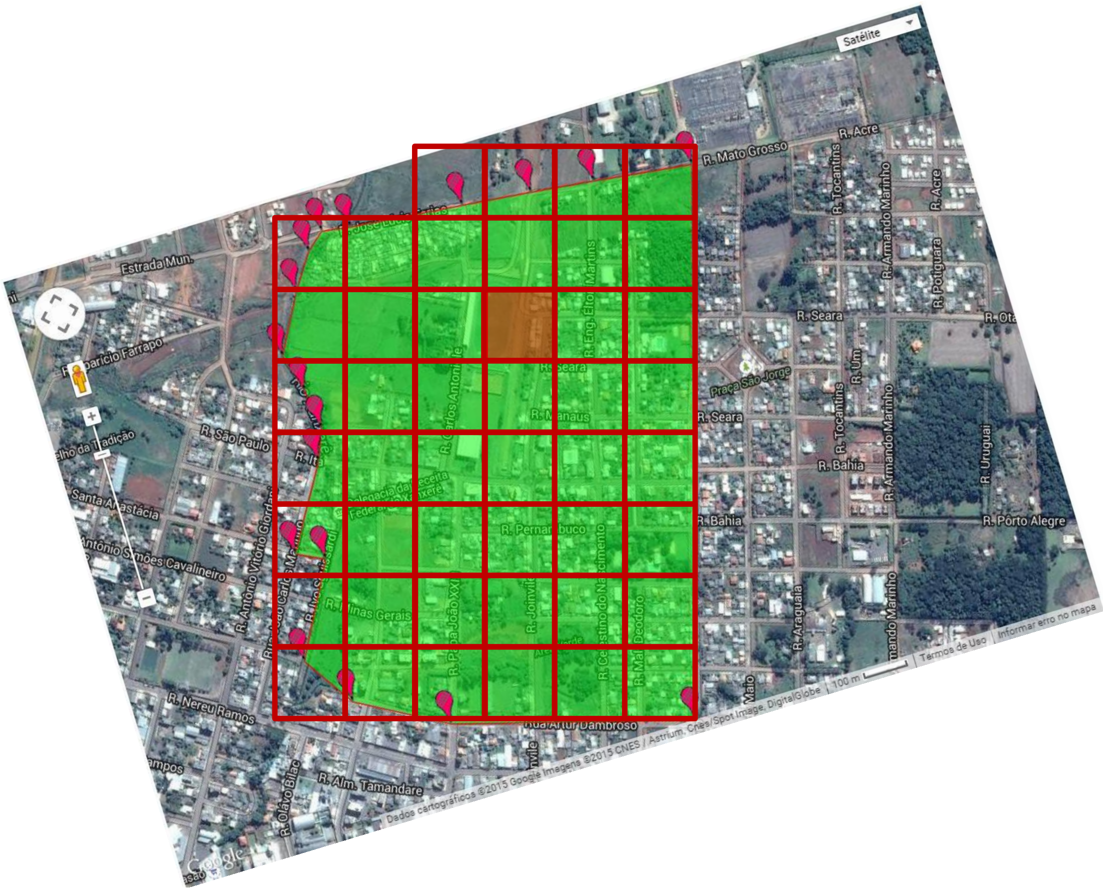

Figure 12: States of the Process

Source: Adapted from Google (2015)

As the affected area (in green in Figure 12) is not perfectly rectangular and the representation of states is a square, the mapped area (red set) become bigger than 0,84km². The total mapped area is 1,03km² instead of 0,84km².

8. **Define the starting point**

   The starting point is the red cell above due to the fact that there is a soccer field over there. It is better to start a flight in an outdoor region with no obstacles than an urban area with many buildings.

9. **Define states priorities**

   The criteria used to define the states priorities in Figure 13 was: priority 1 to the cells with more than 70% of green area (small probability to find victims), priority 2 to cells with half green half occupied area, and priority 3 to cells with more than 70% occupied area (high probability to find victims). We assign a priority class of -1 to the cells which are classified as obstacles. This is to discourage the UAVs from visiting such cells.

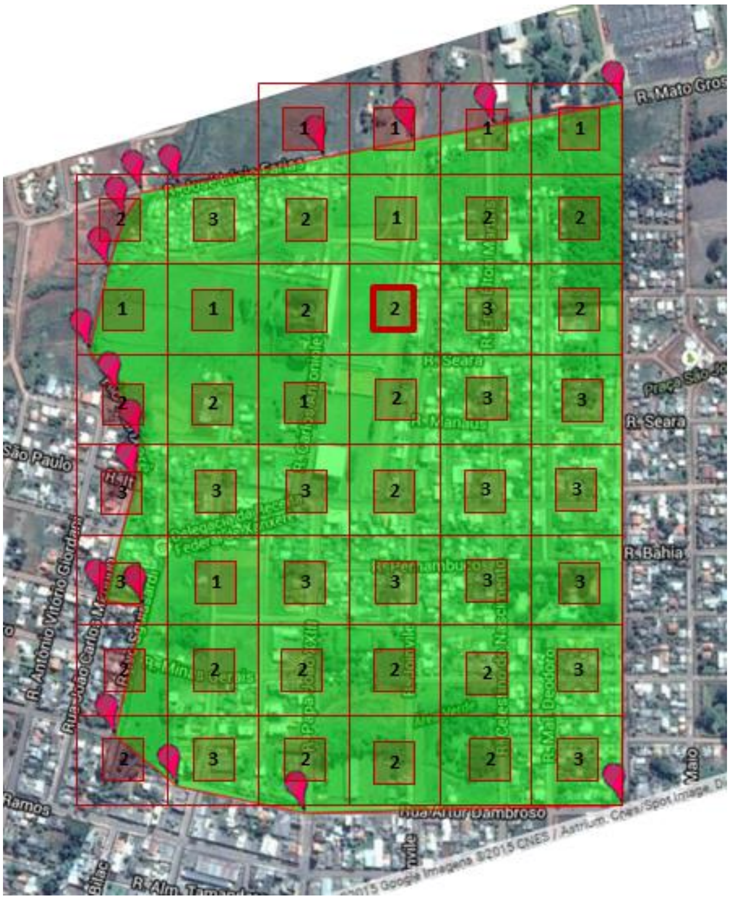

Figure 13: States Priorities

Source: Adapted from Google (2015)

Simulating

1. **Define the states with victims**

   The states will be named from 0 to 45 as shown in Figure 14. The state 46 was created as a obstacle cell to delimitate the area to be flown.

		46	46	46	46	46	46
46	46	46	0	1	2	3	46
46	4	5	6	7	8	9	46
46	10	11	12	13	14	15	46
46	16	17	18	19	20	21	46
46	22	23	24	25	26	27	46
46	28	29	30	31	32	33	46
46	34	35	36	37	38	39	46
46	40	41	42	43	44	45	46
46	46	46	46	46	46	46	46

Figure 14: States with victims

Source: Author

There are victims in cells 5, 6, 14, 20, 26, 27, 31, 32, 37, 38, 39, 41 and 45. These cells have priorities 2 and 3.

Solver

1. **Define the discount factor**

   In this thesis, a 0.95 discount factor will be used (Cassandra, 2015).

2. **Define the states**

   The states will be named from 0 to 45 according to the input file format (see Appendix I).

3. **Define the actions**

   The actions are: go north (N), go south (S), go east (E), go west (W), go north-east (NE), go north-west (NW), go south-east (SE) or go south-west (SW).

4. **Define the observations**

   An observation can be *y* (yes, there is a victmin in the observed area) or *n* (no, there is not a victmin in the observed area). If it is a "yes" observation, then the UAV reports the location (GPS coordinates) via wifi to the ground rescue teams.

5. **Calculate the transition probabilities**

   The transition probabilities for the state 0 are:

   T: n : s0 : s46 1

   T: s : s0 : s6 1

   T: e : s0 : s1 1

   T: w : s0 : s46 1

   T: ne : s0 : s46 1

   T: nw : s0 : s46 1

   T: se : s0 : s7 1

   T: sw : s0 : s5 1

   See https://dl.dropboxusercontent.com/u/105316427/Anexos.docx for the other states.

6. **Define the reward**

   The reward is 1 if the UAV finds a state with victims (*y* observations) and 0 if not (*n* observation).

7. **Define actual state $\boldsymbol{b(s)}$**

   $b(s) = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, \mathbf{1}, 0, 0, 0, 0, 0, \ldots 0]$

   Which means that the probability of the system to be in the state 13 is 1 (or 100%) and the probability of the system to be in any other state is 0 (or 0%).

8. **Calculate belief map**

		1	1	1	1
2	3	2	1	2	2
1	1	2	$\boxed{2}$	3	2
2	2	1	2	3	3
3	3	3	2	3	3
3	1	3	3	3	3
2	2	2	2	2	3
2	3	2	2	2	3

		0,01	0,01	0,01	0,01
0,02	0,03	0,02	0,01	0,02	0,02
0,01	0,01	0,02	$\boxed{0,02}$	0,03	0,02
0,02	0,02	0,01	0,02	0,03	0,03
0,03	0,03	0,03	0,02	0,03	0,03
0,03	0,01	0,03	0,03	0,03	0,03
0,02	0,02	0,02	0,02	0,02	0,03
0,02	0,03	0,02	0,02	0,02	0,03

Figure 15: Belief Map

Source: Author

9. **Write the input file**

The input file (see https://dl.dropboxusercontent.com/u/105316427/Anexos.docx) should be written according to Appendix I.

10. **Execute the solver**

The step-by-step to execute the solver is described in the POMDP ORG (Cassandra, 2015).

11. **Handle output file $R(s,a)$**

The solver output, a set of vectors $R(s,a)$, was handled in Excel to replace dots with commas and to paste the values vertically. The figures 16 and 17 below show the first output treatment.

5

0.00 0.00 0.00

Figure 16: Solver output for the first 3 states before handle in Excel

Source: Author

R(s,5)
0,00
0,00
0,00

Figure 17: Solver output for the first 3 states after handle in Excel

Source: Author

12. Calculate $p(s, a)$

State Probabilities		Reward vector of each action								Reward function of each action							
State (s)	P(s) = b(s)	R(s, 0)	R(s, 1)	R(s, 2)	R(s, 3)	R(s, 4)	R(s, 5)	R(s, 6)	R(s, 7)	R(s, 0)	R(s, 1)	R(s, 2)	R(s, 3)	R(s, 4)	R(s, 5)	R(s, 6)	R(s, 7)
0	0	0,00	0,03	0,02	0,00	0,00	0,00	0,02	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
1	0	0,00	0,02	0,03	0,02	0,00	0,00	0,03	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
2	0	0,00	0,03	0,03	0,02	0,00	0,00	0,03	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
3	0	0,00	0,03	0,00	0,02	0,00	0,00	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
4	0	0,00	0,03	0,04	0,00	0,00	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
5	0	0,00	0,04	0,04	0,05	0,03	0,00	0,04	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
6	0	0,03	0,04	0,03	0,05	0,02	0,00	0,03	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
7	0	0,02	0,03	0,05	0,03	0,03	0,02	0,05	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
8	0	0,03	0,05	0,04	0,03	0,03	0,03	0,04	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
9	0	0,03	0,04	0,00	0,04	0,00	0,03	0,00	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
10	0	0,03	0,03	0,03	0,00	0,04	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
11	0	0,04	0,03	0,03	0,02	0,04	0,03	0,03	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
12	0	0,04	0,03	0,04	0,03	0,03	0,05	0,04	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
13	1	0,03	0,04	0,06	0,04	0,05	0,04	0,06	0,03	0,03	0,04	0,06	0,04	0,05	0,04	0,06	0,03
14	0	0,05	0,06	0,05	0,05	0,04	0,04	0,05	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
15	0	0,04	0,05	0,00	0,05	0,00	0,04	0,00	0,06	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	..
40	0	0,04	0,00	0,03	0,00	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
41	0	0,05	0,00	0,02	0,05	0,04	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
42	0	0,04	0,00	0,02	0,05	0,04	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
43	0	0,04	0,00	0,02	0,04	0,04	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
44	0	0,04	0,00	0,03	0,04	0,06	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
45	0	0,06	0,00	0,00	0,05	0,00	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
46	0	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
									Sum:	0,03	0,04	0,06	0,04	0,05	0,04	0,06	0,03

Figure 18: Calculating reward function of each action multiplying the state probability by the reward vector of each action

Source: Author

13. Calculate max $p(s, a)$

In the example above (Figure 18), the max $p(s, a)$ is 0,06.

14. Act as max $p(s, a)$

Execute the action 2 or 6.

15. Update the traveled cell’s priority to ZERO

		1	1	1	1
2	3	2	1	2	2
1	1	2	**0**	3	2
2	2	1	2	3	3
3	3	3	2	3	3
3	1	3	3	3	3
2	2	2	2	2	3
2	3	2	2	2	3

Figure 19: Belief map updated

Source: Author

16. If the UAV found victims (y observation), increase not-traveled-neighbour-cells priority 1 unit until the sum of belief map be ZERO.

After repeating steps 8 to 15 of the Solver process above (until the sum of belief map is zero), some statistics can present the efficiency of the algorithm. The simulation was repeated 5 times, with the same simulation scenario, and the rounds will be named as S1, S2, S3, S4 e S5. The figures 20, 21, 22 and 23 show the results.

Statistics

- Calculate traveled distance

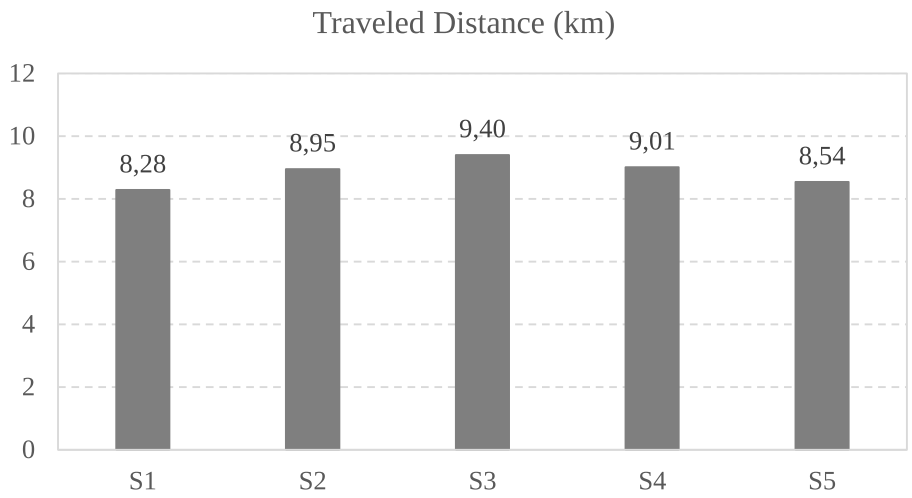

Figure 20: Traveled Distance (km)

Source: Author

- Calculate operation's duration

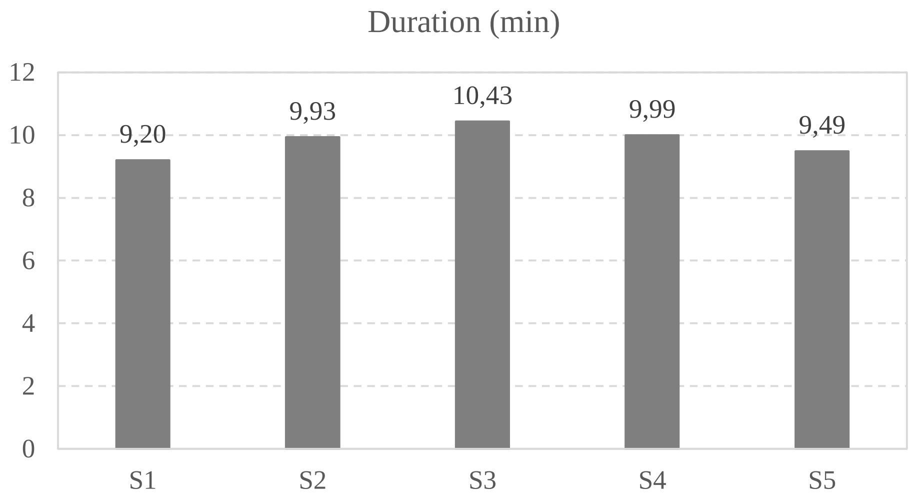

Figure 21: Duration (min)

Source: Author

- Calculate coverage percentage

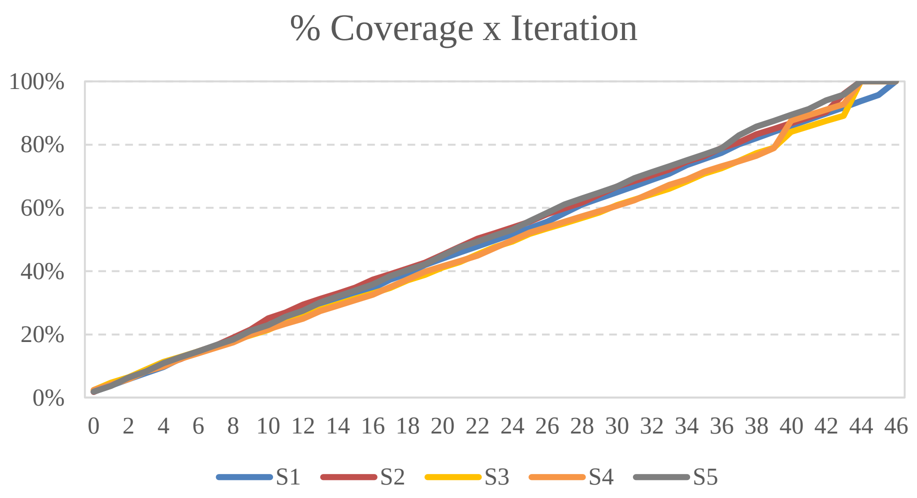

Figure 22: % Coverage

Source: Author

- Calculate time to find groups of victims (G1, G2, …, G13)

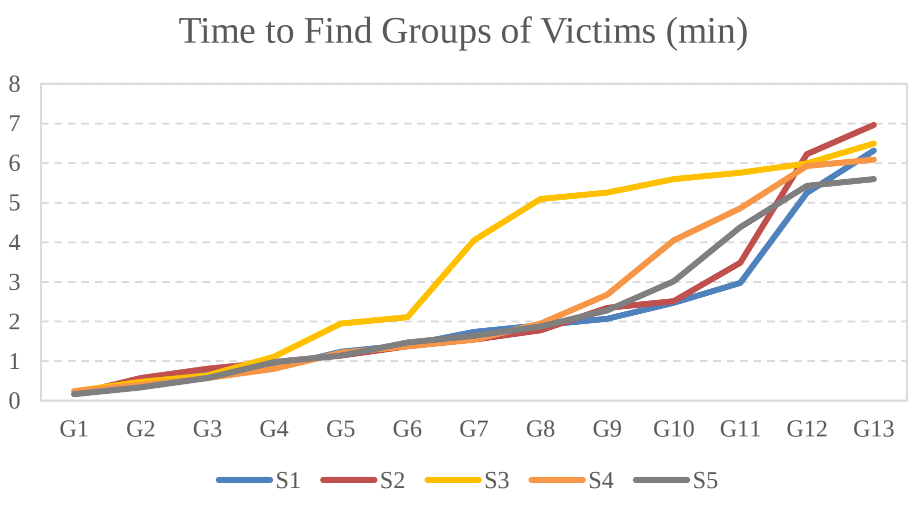

Figure 23: Time to Find Groups of Victims (min)

Source: Author

Comparing with Greedy Algorithm

In the first simulation of the greedy algorithm, the coverage percentage achieved 52% of the total area which means that the UAV traveled only through 24 of the 46 states. Once a UAV misses some cell near the start location to move towards high priority areas, it is very hard for it to come back to cover it later.

Forcing the greedy algorithm to travel the entire area, the results showed that the average traveled distance of the greedy is 0.3 km more than POMDP (Figure 24), the average operation's duration is 0.33 minutes more than POMDP (Figure 25) and the average time to find groups of victims is 2 minutes more than POMDP (Figure 26).

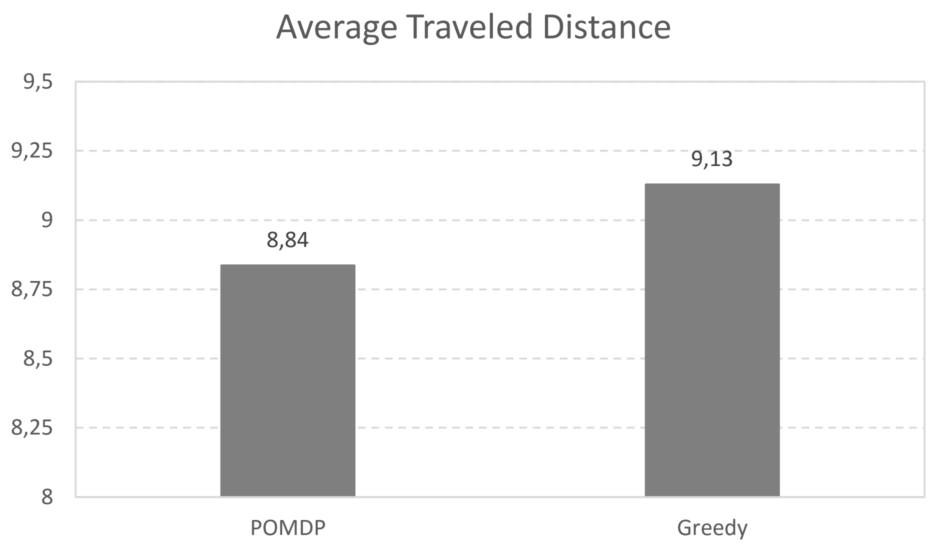

Figure 24: Average Traveled Distance (POMDP x Greedy)

Source: Author

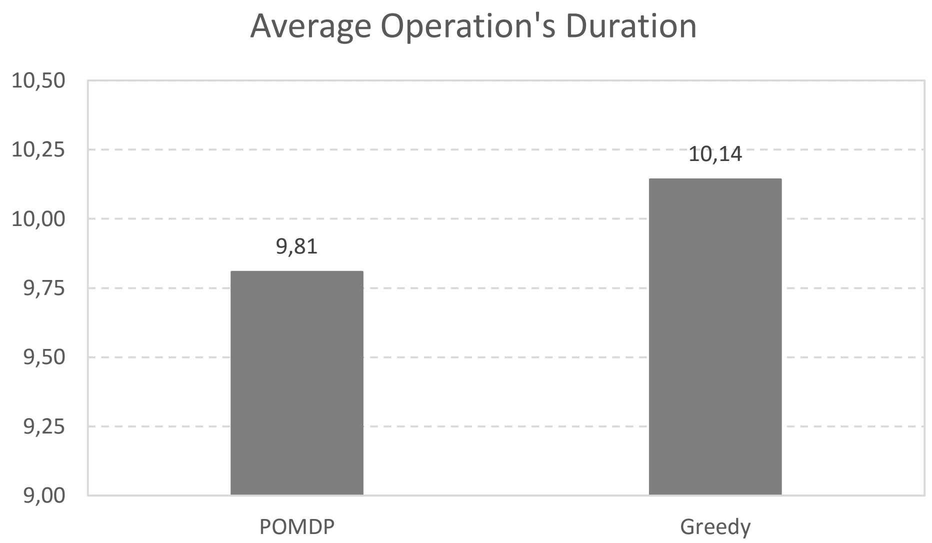

Figure 25: Average Operation's Duration (POMDP x Greedy)

Source: Author

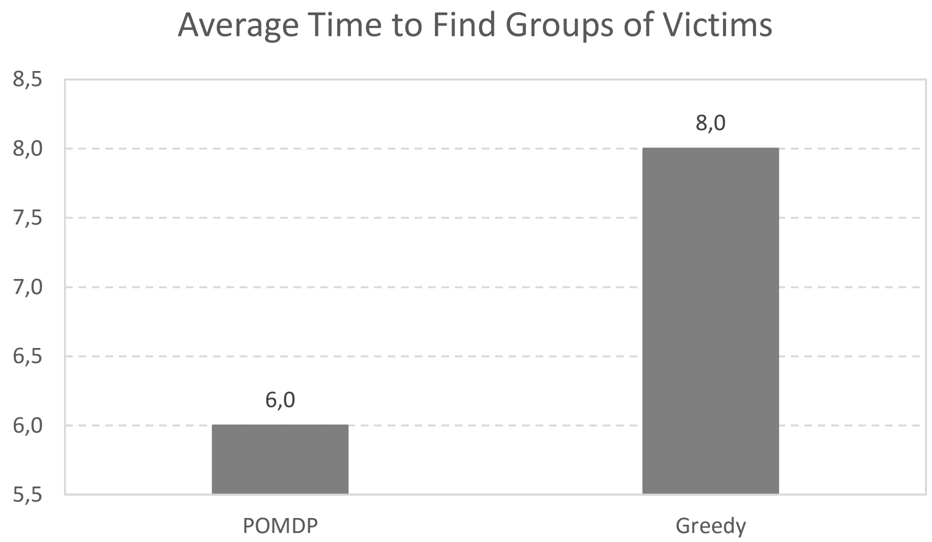

Figure 26: Average Time to Find Groups of Victims (POMDP x Greedy)

Source: Author

The most significant difference is in the time to find groups of victims, where POMDP has a 20% faster performance than greedy, due to the fact that the POMDP has the bias to save lifes, updating its belief at each iteration through observations while the greedy focuses on minimizing the traveled distance.

These 2 minutes, which represent 25% of total operation's duration, can realy make difference in saving lives. If the victim suffers from a cardiac arrest, for example, one minute can increase chance of survival from 8% to 80% (Momont, 2014).

In this section, the Xanxerê's coverage problem was defined based on partial knowledge of terrain beforehand. We prioritize the cells according to probability of having victims and propose a solution to this constrained coverage problem based on POMDP. The results showed that the mapping of the affected region can be made in less than 10,5 minutes and the coverage is 100% in every simulation. A comparison with greedy algorithm showed that POMDP has a better performance mostly in terms of time to find groups of victims.

5.2 BOR PoC – Refugee’s Camp, South Sudan

According to UNHCR (2015), since the outbreak of the conflict in South Sudan in December 2013, continuing insecurity, and logistical constraints owing to heavy rains, have hampered the delivery of food and other essential items. Access to displaced people has been restricted, and refugees have faced serious protection concerns. At the same time, humanitarian workers have been at heightened risk. Six humanitarian workers were killed in a refugee-hosting area of Maban County in August 2014.

The multiplicity of armed elements throughout South Sudan greatly exacerbated the challenge of re-establishing the civilian character of refugee’s camps in the north and north-east of the country. This also affected the protection of the environment with the erosion of law and order in refugee settlements and camps, as well as in surrounding communities (UNHCR, 2015).

Competition over scarce resources has in some places caused tensions and fighting between refugees and host communities. Greater attention must be paid to the needs of host communities in order to foster peaceful coexistence. This is important in order to minimize the risk of secondary displacement of refugees and further instability in the border regions (UNHCR, 2015).

Insecurity and access constraints have required the use of air transport for goods and humanitarian personnel, driving up the costs of delivering assistance and services to refugees and the internally displaced people (IDPs). The crisis has also stymied plans to improve camp-based refugees' living conditions through the upgrading of emergency structures into more organized, sustainable constructions (UNHCR, 2015).

The South Sudanese civilian population at large is bearing the brunt of the conflict, with some 1.4 million people uprooted by the end of September 2014. The continuing violence could also precipitate famine in the country, where millions suffer from food insecurity and varying degrees of malnutrition as they cannot plant, grow and harvest crops due to their forced displacement (UNHCR, 2015)..

According to Reach (2015), the Bor protection of civilian (PoC) site was established in December 2013 following outbreaks of violence which forced people into the UNMISS base for refuge. The PoC was relocated to the new Bor PoC Site in September 2014.

After defining the disaster area, the methodology proposed in chapter 4 will be applied to create the drone path planning.

Modeling

1. **Define the affected area to be flown**

   BOR PoC – a refugee's camp in South Sudan.

2. **Calculate the area of affected region**

   According to Reach (2015), the area of BOR PoC refugee's camp is 80905 m² or 0,080905 km². See Figure 27.

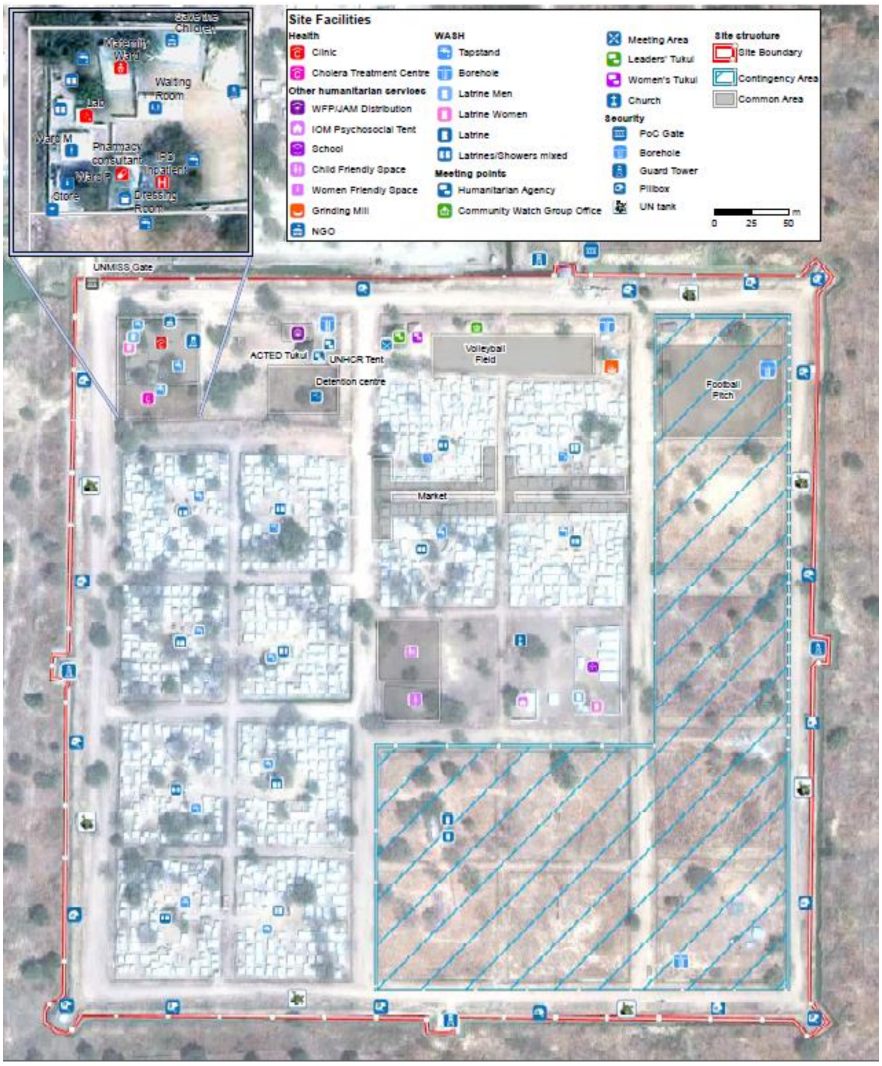

Figure 27: BOR PoC Area

Source: Adapted from Reach (2015)

3. **Choose the type of UAV**

   Accordingly to Bento (2008), tactical UAVs are recommended for search and rescue operations. However the mini/micro UAVs will be used because it has a sufficient data link range for BOR PoC area and it has a lower operation cost.

4. **Define the average flight height**

   This example will work with an average flight height of 150m.

5. **Define the camera to be used**

   In this example, a Nikon D7000 camera was considered.

6. **Calculate the area representing the states of the process**

   As the average flight height is 150m and a Nikon D7000 is the camera - it has a 36,8º angle – we can calculate the area from which the UAV can capture images with sufficient resolution to identify affected people. See Figure 28.

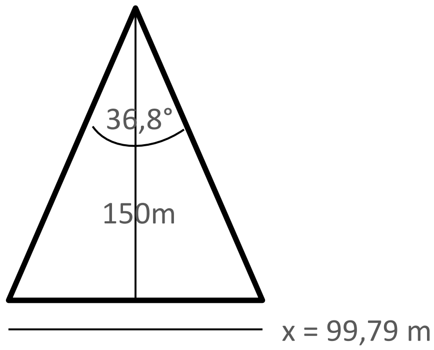

Figure 28: Nikon D7000 Image Resolution

Source: Author

To be conservative, it will be used an area of 90m x 90m instead of 99,79m x 99,79m. Then, the area representing each state is 1.800m².

7. **Divide the region to be flown in the states of the process**

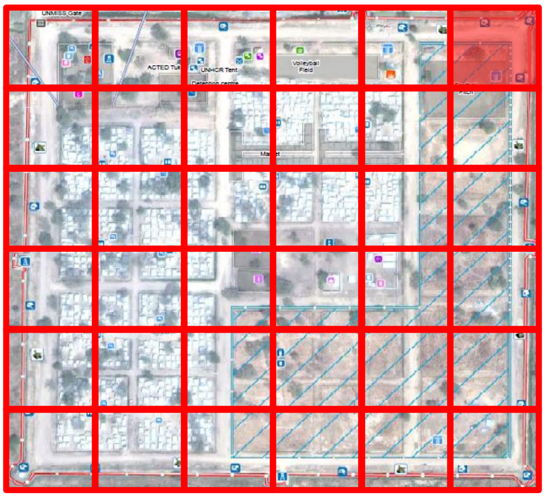

Figure 29 States of the Process

Source: Adapted from Reach (2015)

8. **Define the starting point**

   The starting point is the red cell above (Figure 29) due to the fact that there is a football pitch over there.

9. **Define states priorities**

   The criteria used to define the states priorities in Figure 30 was: priority 1 to the cells with contingency area or with volleyball field (small probability to find victims), priority 2 to cells with half contingency half occupied area or to cells with clinics, WFP center, pharmacy, labs, and priority 3 to cells with occupied area (high probability to find victims). We assign a priority class of -1 to the cells which are classified as obstacles. This is to discourage the UAVs from visiting such cells.

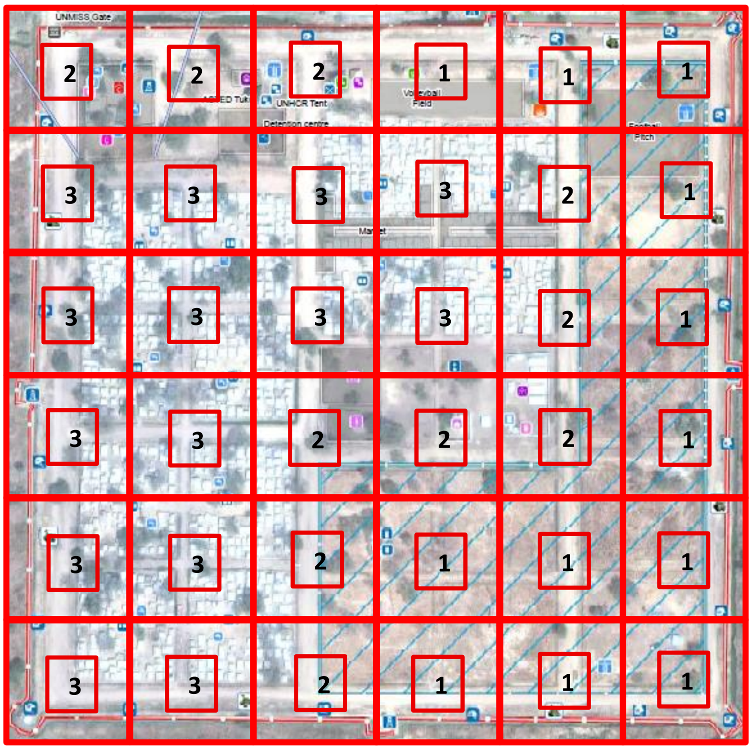

Figure 30: States Priorities

Source: Adapted from Google

Simulating

1. **Define the states with victims**

   The states will be named from 0 to 35 as shown in Figure 31. The state 36 was created as a obstacle cell to delimitate the area to be flown.

36	36	36	36	36	36	36	36
36	0	1	2	3	4	5	36
36	6	7	8	9	10	11	36
36	12	13	14	15	16	17	36
36	18	19	20	21	22	23	36
36	24	25	26	27	28	29	36
36	30	31	32	33	34	35	36
36	36	36	36	36	36	36	36

Figure 31: States with victims

Source: Author

There are victims in cells 56, 7, 8, 9, 10, 12, 13, 14, 15, 16, 18, 19, 20, 24, 25, 26, 30, 31 and 32. These cells have priorities 2 and 3.

Solver

1. **Define the discount factor**

   In this thesis, a 0.95 discount factor will be used (Cassandra, 2015).

2. **Define the states**

   The states will be named from 0 to 35 according to input file format (see Appendix I).

3. **Define the actions**

   The actions are: go north (N), go south (S), go east (E), go west (W), go north-east (NE), go north-west (NW), go south-east (SE) or go south-west (SW).

4. **Define the observations**

   An observation can be *y* (yes, there is a victmin in the observed area) or *n* (no, there is not a victmin in the observed area). If it is a “yes” observation, then the UAV reports the location (GPS coordinates) via wifi to the ground rescue teams.

5. **Calculate the transition probabilities**

   The transition probabilities for the state 0 are:

   T: n : s0 : s46 1

   T: s : s0 : s6 1

T: e : s0 : s1 1

T: w : s0 : s46 1

T: ne : s0 : s46 1

T: nw : s0 : s46 1

T: se : s0 : s7 1

T: sw : s0 : s46 1

See https://dl.dropboxusercontent.com/u/105316427/Anexos.docx for the other states.

6. Define the reward

The reward is 1 if the UAV finds a state with victims (*y* observations) and 0 if not (*n* observation).

7. Define actual state $\boldsymbol{b(s)}$

$b(s) = [0, 0, 0, 0, 0, \mathbf{1}, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, \ldots 0]$

Which means that the probability of the system to be in the state 5 is 1 (or 100%) and the probability of the system to be in any other state is 0 (or 0%).

8. Calculate belief map

2	2	2	1	1	1
3	3	3	3	2	1
3	3	3	3	2	1
3	3	2	2	2	1
3	3	2	1	1	1
3	3	2	1	1	1

0,03	0,03	0,03	0,01	0,01	0,01
0,04	0,04	0,04	0,04	0,03	0,01
0,04	0,04	0,04	0,04	0,03	0,01
0,04	0,04	0,03	0,03	0,03	0,01
0,04	0,04	0,03	0,01	0,01	0,01
0,04	0,04	0,03	0,01	0,01	0,01

Figure 32: Belief Map

Source: Author

The values presented in Figure 32 are rounded.

9. Write the input file

The input file (see https://dl.dropboxusercontent.com/u/105316427/Anexos.docx) should be written according to Appendix I.

10. Execute the solver

The step-by-step to execute the solver is described in the POMDP ORG (Cassandra, 2015).

11. Handle output file $\boldsymbol{R(s,a)}$

The solver output, a set of vectors $R(s,a)$, was handled in Excel to replace dots with commas and to paste the values vertically. The figures 33 and 34 below show the first output treatment.

5
0.00 0.00 0.00

Figure 33: Solver output for the first 3 states before handle in Excel

Source: Author

R(s,5)
0,00
0,00
0,00

Figure 34: Solver output for the first 3 states after handle in Excel

Source: Author

12. Calculate $\boldsymbol{p(s,a)}$

State Probabilities		Reward vector of each action								Reward function of each action							
Estado (s)	P(s) = b(s)	R(s, 0)	R(s, 1)	R(s, 2)	R(s, 3)	R(s, 4)	R(s, 5)	R(s, 6)	R(s, 7)	R(s, 0)	R(s, 1)	R(s, 2)	R(s, 3)	R(s, 4)	R(s, 5)	R(s, 6)	R(s, 7)
0	0	0,00	0,04	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
1	0	0,00	0,04	0,03	0,03	0,00	0,00	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
2	0	0,00	0,04	0,01	0,03	0,00	0,00	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
3	0	0,00	0,04	0,01	0,03	0,00	0,00	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
4	0	0,00	0,03	0,01	0,01	0,00	0,00	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
5	1	0,00	0,01	0,00	0,01	0,00	0,00	0,00	0,03	0,00	0,01	0,00	0,01	0,00	0,00	0,00	0,03
6	0	0,03	0,04	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
7	0	0,03	0,04	0,04	0,04	0,00	0,03	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
8	0	0,03	0,04	0,04	0,04	0,00	0,03	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
9	0	0,01	0,04	0,03	0,04	0,00	0,03	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
10	0	0,01	0,03	0,01	0,04	0,00	0,01	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
11	0	0,01	0,01	0,00	0,03	0,00	0,01	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
12	0	0,04	0,04	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
13	0	0,04	0,04	0,04	0,04	0,00	0,04	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
14	0	0,04	0,03	0,04	0,04	0,00	0,04	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
15	0	0,04	0,03	0,03	0,04	0,00	0,04	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
30	0	0,04	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
31	0	0,04	0,00	0,03	0,04	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
32	0	0,03	0,00	0,01	0,04	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
33	0	0,01	0,00	0,01	0,03	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
34	0	0,01	0,00	0,01	0,01	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
35	0	0,01	0,00	0,00	0,01	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
36	0	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
									Sum	0,00	0,01	0,00	0,01	0,00	0,00	0,00	0,03

Figure 35: Calculating reward function of each action multiplying the state probability by the reward vector of each action

Source: Author

13. Calculate max $\boldsymbol{p(s, a)}$

In the example above (Figure 35), the max $\boldsymbol{p(s, a)}$ is 0,03.

14. Act as max $\boldsymbol{p(s, a)}$

Execute the action 7.

15. Update the traveled cell's priority to ZERO

2	2	2	1	1	0
3	3	3	3	2	1
3	3	3	3	2	1
3	3	2	2	2	1
3	3	2	1	1	1
3	3	2	1	1	1

Figure 36: Belief map updated

Source: Author

16. If the UAV found victims (y observation), increase not-traveled-neighbour-cells priority 1 unit until the sum of belief map be ZERO.

After repeating steps 8 to 15 of the Solver process above (until the sum of belief map is zero), some statistics can present the efficiency of the algorithm. The simulation was repeated 5 times and the rounds will be named as S1, S2, S3, S4 e S5. Figures 37, 38, 39 and 40 show the results.

Statistics

- Calculate traveled distance

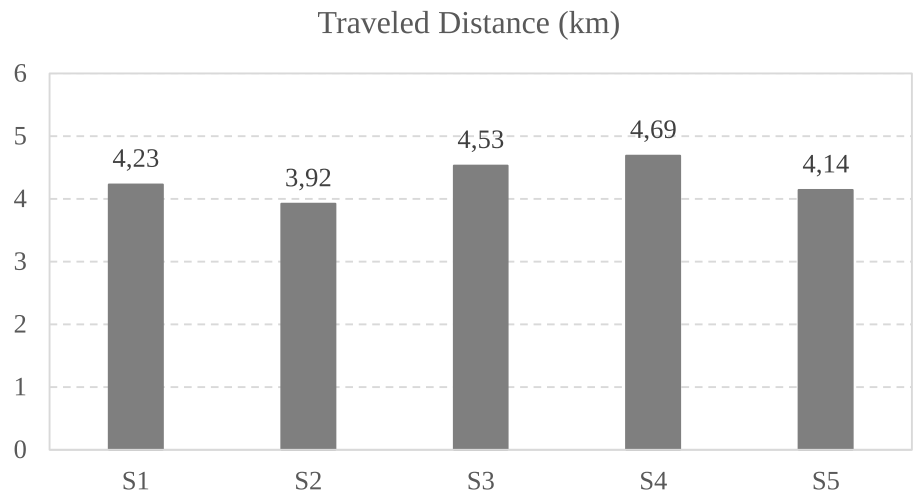

Figure 37: Traveled Distance (km)

Source: Author

- Calculate operation’s duration

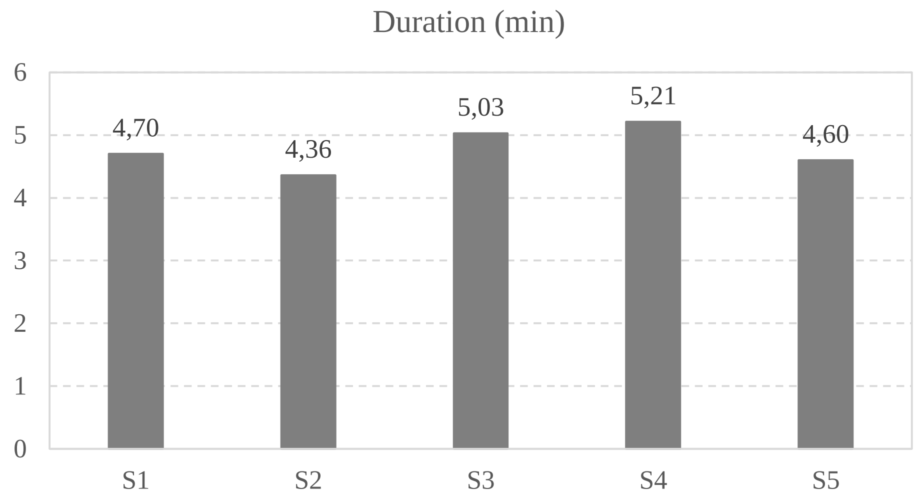

Figure 38: Duration (min)

Source: Author

- Calculate coverage percentage

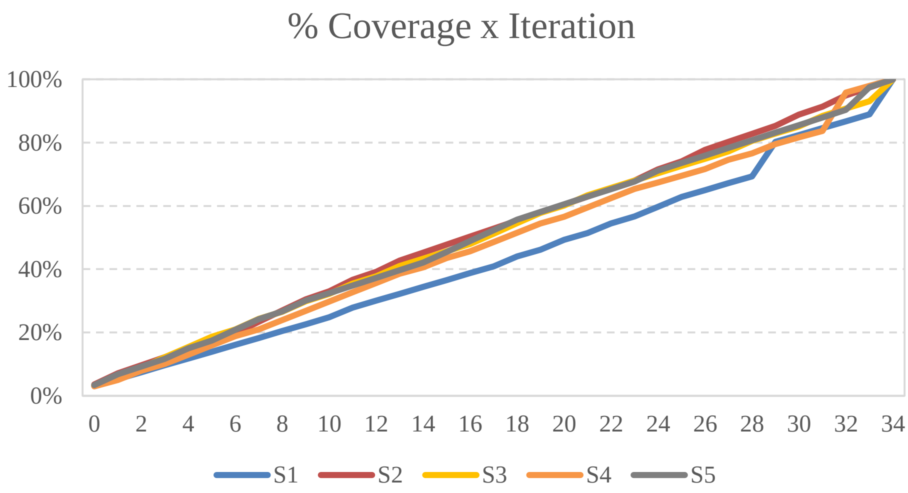

Figure 39: % Coverage

Source: Author

- Calculate time to find groups of victims (G1, G2, …, G13)

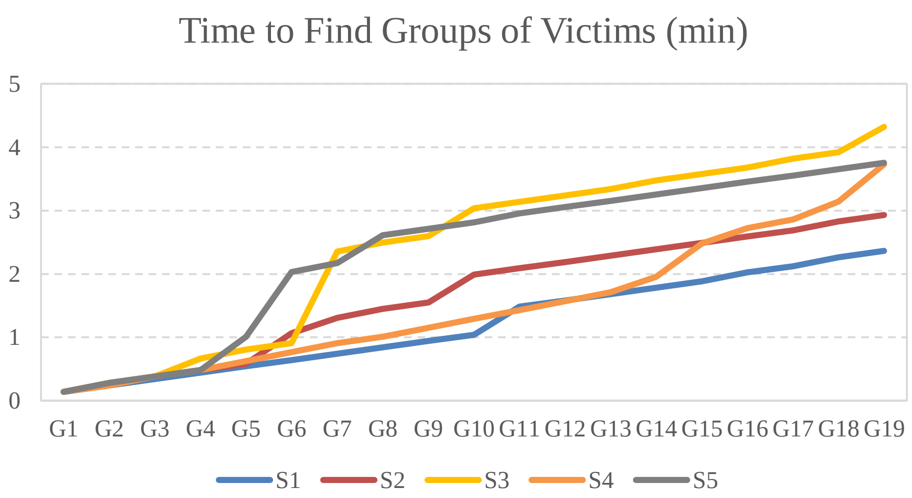

Figure 40: Time to Find Groups of Victims (min)

Source: Author

Comparing with Greedy Algorithm

As the area of Bor PoC is ten times smaller than Xanxerê, the difference between the POMDP and the greedy was not significant in terms of traveled distance and operation's duration. The average time to find groups of victims with greedy took 1 minute more than POMDP which means that POMDP performed 25% better. See Figure 41.

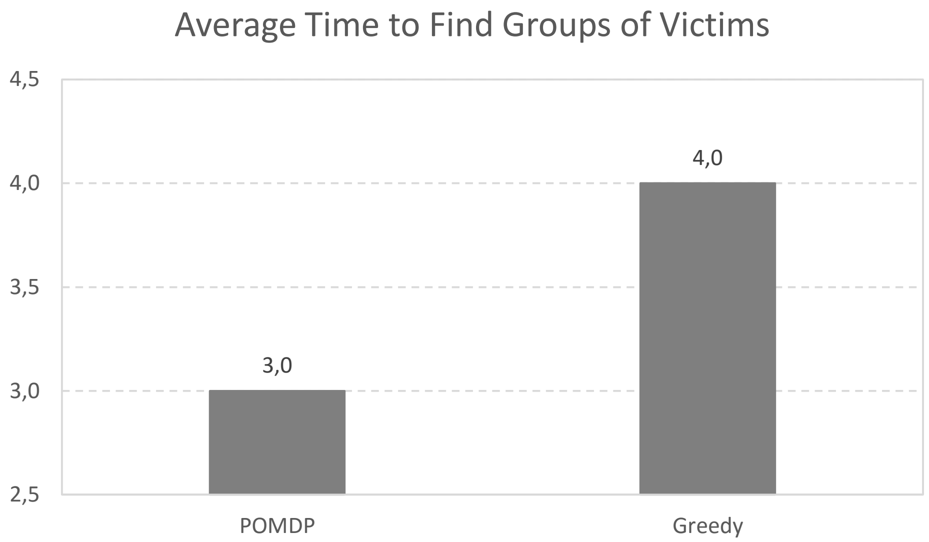

Figure 41: Average Time to Find Groups of Victims (POMDP x Greedy)

Source: Author

In this section, the Bor PoC coverage problem was defined based on partial knowledge of terrain beforehand. We prioritize the cells according to probability of having victims and propose a solution to this constrained coverage problem based on POMDP. The results showed that the mapping of the affected region can be made in less than 5,5 minutes and the coverage is 100% in every simulation. Comparing with greedy algorithm, POMDP has no significantly better results in traveled distance and operation's duration because of the small area, differently of Xanxerê's example. The larger the area, the greater the difference in performance of these statistics. On the other hand, the average time to find groups of victims was 25% faster in POMDP heuristic.

5.3 Discussion

After applying the proposed methodology in two illustrative examples, the statistics presented a 100% coverage percentage in both cases, which means that the algorithm has been successfully implemented in a rapid-onset and in a slow-onset disaster.

The traveled distance and the operation's durations did not have a significative standard deviation between the five simulations in each example, even if the paths were different (each path is available at (https://dl.dropboxusercontent.com/u/105316427/Anexos.docx). It means that even if there were many possible paths, due to the tied priorities, the algorithm has homogeneous results. See Figure 42 and 43. The entire affected area was traveled in less than 10 minutes, in the Xanxerê's example, and in less than 5 minutes, in Bor PoC example.

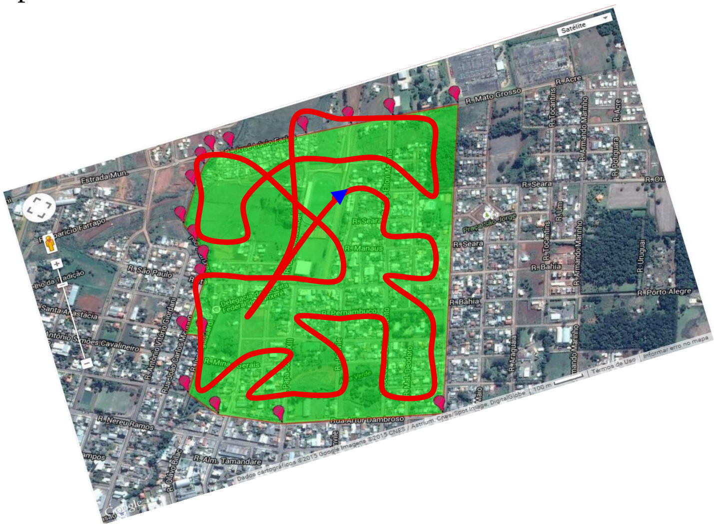

Figure 42: Xanxerê's Path Planning (Simulation 1)

Source: Author

Figure 43: Xanxerê's Path Planning (Simulation 5)

Source: Author

On the other hand, the time to find groups of victims is completely variable and susceptible to the state's priorities. If the priorities were set by a non-specialist, the algorithm can firstly direct the UAV to areas with no victims. In this case, the search and rescue operation will not be successfully implemented, because it is not saving lifes as soon as possible.

The affected area of Bor PoC was ten times smaller than Xanxerê's but the average traveled distance and the average operation's duration were just two times smaller than Xanxerê's, which means that they are not directly proportional to the affected area only, it also depends on the number of states. If the flight height in Bor PoC example was the same as Xanxerê example, the number of states would be 10 instead of 37 and then the traveled distance and operation's duration would be smaller.

Murtaza *et al.* (2013) has also compared the POMDP algorithm with the greedy but the simulations included three scenarios: a practical placement scenario, a mixed placement scenario and a worst placement scenario. The results, in all of them, which were measured as percentual coverage and time to find groups of victims, showed that POMDP achieved 100% of the affected area while greedy did not. The time to find groups of victims was just a few seconds less in POMDP but their theorical application has just 225m². There is no percentage of performance improvement because the paper just shows comparative graphics, without numbers.

Meier (2014) affirms that very small and lightweight UAVs will be used in disaster response for micro-transportation soon. As the POMDP algorithm identify the areas with victims, it could be used as a micro-transport delivering emergency materials such as medicines and supplies for the affected people.

6 Conclusions

This dissertation provides a POMDP based methodology for finding victims in disaster affectd areas with UAVs. In a disaster situation, the number of victims is unknown, so the UAV path planning becomes similar to an area coverage problem, since it has to search through the entire affected area to find the victims. Given this consideration, the UAV path planning is a very important task for saving victim's lifes.

In this study, the coverage problem is based on partial knowledge of the terrain before hand. The cells were prioritised according to their location and the solution to this constrained coverage problem was based on a Markov decision process. The POMDP considers that actions are based only on the available information, that consists of previous observations and actions, and can provide an optimal path planning for UAVs to move from a starting position to the highest priority area in order to maximize the reward. Motivated by this, a methodology to guide UAVs through the entire affected area is proposed.

This methodology has an innovative character, as the systematic literature review did not present any study with this purpose. An increase in the number of publications about the applications of UAVs in humanitarian relief over the past ten years was presented on a systematic literature review on chapter 3. Only one author of this area is studying the use of drones in emergency situations although humanitarian relief is a recent and growing area. Mostly contributions in this area are to improve the equipment's performance and comes from robotic and mechanical engineering. In the section 3.3.1, 117 papers were surveyed, classified, and some gaps were identified, allowing suggestions for future research. The conclusions are the need for more studies about mitigation and preparedness and the small number of papers on man-made and slow-onset disasters. It is important to reinforce that UAV is a promising technology, which is still being technically developed, that have positive impact in humanitarian settings and is already being used by private organizations, such as Google, to test and improve their methodologies, algorithms and models.

Chapter 3 has also showed that the use of the POMDP technique applied to drones involves optimization of the communication among UAVs, multi-target detection and recognition, and SO-based (Self-Organized-based) autonomous vehicles. Simulation applications in Humanitarian Logistics has the bias to test the models and algorithms developed. Although these solutions are used in very specific ways, they together have a potential application for humanitarian relief.

The methodology proposed in this disseration consists of four steps. The first step is to model the problem defining the affected area, the type of UAV, the camera resolution, the starting point, the states priorities and the area of the states. The simulation is the second step where victims need to be addressed in order to test the efficiency of the algorithm. Then, the solver can be initialized and the UAV will travel the entire affected area looking forward to finding victims. Finally, the last step measures the results through the following statistics: traveled distance, operation’s duration, coverage percentage and time to find groups of victims.

In order to test the efficiency of the POMDP solution, Chapter 5 presents two illustrative examples: Xanxerê’s tornado, which is a rapid-onset disaster, and Bor PoC refugee’s camp, in South Sudan, a slow-onset disaster. After five simulations in each example, it was shown that the proposed solution achieves 100% coverage while optimizing the time to find victims as well. The conclusions included the need of a specialist to set the state’s priorities, so the algorithm can firstly direct the UAV to areas with victims, and be successfully implemented saving lifes as soon as possible. It was reinforced that the number os states is crucial for determing the UAV’s traveled distance and operation’s duration, which should be realistic and mechanically viable statistics.

Future research should implement the proposed methodology in disasters with a large area such as hurricane Sandy and typhoon Haiyan. In this cases, the POMDP output file and the excel sheets should be integrated and automated, and more than one UAV should be used, as the autonomy will become a constraint to the algorithm in terms of traveled distance and operation’s duration. A sensitivity analysis is also recommended in order to measure the variation in the statistics from the number of states, for example. A practical application is also a possible future research as the UAVs nowadays are programmable, so the algorithm can be implemented in a real UAV. The area to be flown for practical applications should attend its regional legal questions, so the recommendation would be using a private terrain or a military area.

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Appendix I: POMDP Solve – Input File Format

According to Cassandra (2015), there are 5 lines that must appear at the beginning of the .pomdp input file. They may appear in any order as long as they precede all specifications of transition probabilities, observation probabilities and rewards.

```
discount: %f
values: [ reward, cost ]
states: [ %d, <list-of-states> ]
actions: [ %d, <list-of-actions> ]
observations: [ %d, <list-of-observations> ]
```

The definition of states, actions and/or observations can be either a number indicating how many there are or it can be a list of strings, one for each entry. These mnemonics cannot begin with a digit. For instance, both:

```
actions: 4
actions: north south east west
```

will result in 4 actions being defined. The only difference is that, in the latter, the actions can then be referenced in this file by the mnemonic name. Even when mnemonic names are used, later references can use a number as well, though it must correspond to the positional numbering starting with 0 in the list of strings. The numbers are assigned consecutively from left to right in the listing starting with zero.

When listing states, actions or observations one or more whitespace characters are the delimiters (space, tab or newline). When a number is given instead of an enumeration, the individual elements will be referred to by consecutive integers starting at 0.

After the preamble, there is the optional specification of the starting state. There are a number of different formats for the starting state. You can either:

- enumerate the probabilities for each state,
- specify a single starting state,
- give a uniform distribution over states, or
- give a uniform distribution over a subset of states.

For the last one, you can either specific a list of states too be included, or a list of states to be excluded. Examples of this are:

```
start: 0.3 0.1 0.0 0.2 0.5

start: uniform

start: first-state

start: 5

start include: first-state third state

start include: 1 3

start exclude: fifth-state seventh-state
```


After the initial five lines and optional starting state, the specifications of transition probabilities, observation probabilities and rewards appear. These specifications may appear in any order and can be intermixed. Any probabilities or rewards not specified in the file are assumed to be zero.

You may also specify a particular probability or reward more than once. The definition that appears last in the file is the one that will take effect. This is convenient for specifying exceptions to a more general specification.

To specify a single, individual transition probability:

```
T: <action> : <start-state> : <end-state> %f
```

The observational probabilities are specified in a manner similar to the transition probabilities. To specify individual observation probabilities:

```
O : <action> : <end-state> : <observation> %f
```

To specify an individual reward:

```
R: <action> : <start-state> : <end-state> : <observation> %f
```

After execute the POMDP-Solve with the .pomdp file format, the solver will generate a .alpha file (or value function file) as an output.

Appendix II: POMDP Solve – Output File Format

The format is simply:

```
A
V1 V2 V3 ... VN

A
V1 V2 V3 ... VN

...
```

Where A is an action number and the V1 through VN are real values representing the components of a particular vector that has the associated action. Note that the length of the lists needs to be equal to the number of states in the POMDP.

To find which action is the "best" for a given set of alpha vectors, the belief state probabilities would be use in a dot product against each alpha vectors coefficients. The vector with the highest value is the winner and the action associated with that vector is the best action to take for that belief state given that value function.

In the chapter 4, we will see an experiment using this POMDP-solver and these file formats, where the POMDP technique will be used as a route algorithm for a drone to find victims after a disaster.