Parametric statistical model checking of UAV flight plan

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Abstract. Unmanned Aerial Vehicles (UAV) are now widespread in our society and are often used in a context where they can put people at risk. Studying their reliability, in particular in the context of flight above a crowd, thus becomes a necessity. In this paper, we study the modelling and analysis of UAV in the context of their flight plan. To this purpose, we build a parametric probabilistic model of the UAV and use it, as well as a given flight plan, in order to model its trajectory. This model takes into account parameters such as potential filter or sensor failure as well as wind force and direction. Because of the nature and complexity of the successive obtained models, their exact verification using tools such as PRISM or PARAM is impossible. We use a new approximation method, called Parametric Statistical Model Checking, in order to compute failure probabilities. This method has been implemented in a prototype tool, which we use to resolve complex issues in a practical case study.

1 Introduction

Unmanned Aerial Vehicles (UAV) are more and more present in our lives through entertainment activities or industrial activities. Therefore they can be dangerous for their environment, for instance in case of a failure when an UAV (aka a drone) is flying above a crowd. In this context, we are working with the PIXIEL[3] company to build a reliable UAV control system. PIXIEL is a company expert in public performances including UAVs, and is in particular known for developing a public performance in the French entertainment park called "Puy du Fou" that includes both human actors and drones.

There are many works dedicated to the study of UAVs. In [10] Koppány Máthé and Lucian Buşoniu study the functioning of a drone. UAV movement recognition is studied in [3], while automatic landing on target is described in [8] and monitoring and conservation are dealt with in [4]. Some works also try to detect breakdowns and malfunctions that can impact drones. We can mention *inter alia*, the detection of communication errors in a multi-drone framework studied in [6] or the development of a basic diagnosis model for solving system issues in [2]. However, to the best of our knowledge, there are no existing works on the parametric study of the impact of component inaccuracy on UAV trajectory.

In order to study and improve the reliability of the drone control system and its safety with respect to the public audience, we perform a rigorous study of the control system in the context of a given flight plan. Our focus is to compute the probability that the actual drone trajectory is far enough from the flight plan that it may endanger the public. To this intent, we decompose the drone system into its main components and study their reliability and accuracy. In particular, we focus on the component that is mostly responsible for deviations in the drone trajectory: the sensors and filter. The Flight Control System (FCS) of the drone is modelled using a parametric Markov Chain (pMC), where the parameters represent levels of inaccuracy of the estimated position of the drone. We then use this model in order to compute the parametric probability that the drone trajectory deviates from the intended flight plan. Exact verification techniques such as those implemented in existing model checking tools for pMCs such as PRISM [7] or PARAM [5] are unsuccessful due to the complexity and size of our model. We therefore use a new technique called parametric Statistical Model Checking, that allows us to approximate this probability in the form of a polynomial function of the parameters.

In Section 2, we briefly explain how we built our formal model. Section 3 then gives the a brief intuition for parametric SMC. Finally, Section 4 presents the results of our experiments using the prototype tool we developed.

[3] `https://www.pixiel-group.com/`

2 Building UAV Model

In this section, we start by reviewing the main components of the drone system and explaining the property we want to verify. We then propose a formal model of the drone that allows to compute its effective trajectory.

2.1 Flight Control System

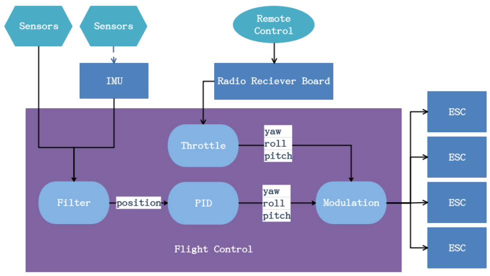

Fig. 1: Flight Control Overview

Since we are interested in computing the effective drone trajectory, the Flight Controller (FC) is the main component of interest in UAV systems. This component indeed allows to collect data from sensors, compute from this data the position of the drone and, using the given flight plan, control the signals sent to the motors in order to move the drone in the right direction. An abstract description of the flight controller is given in Figure 1. As one can see, the FC can also be decomposed into four main components. In the automated flight mode, only three of them are of interest: Filter, PID and Modulation. Filter is the component that receives the data from sensors and cleans this data in order to enhance its accuracy. PID is the component that computes the drone position according to the data received from the filter and computes the commands that are then sent to the motors through modulation.

Apart from component failure (which we do not consider here), the only reason why a drone could deviate from its flight plan is when the estimated position of the drone is inaccurate, resulting in erroneous commands sent to the motors. Such an inaccurate estimated position occurs when the data sent from the sensors is erroneous and/or when the correction produced by the filter is ineffective. In our formal model, we therefore introduce parameters that represent the probability that the estimated position of the drone is inaccurate: $F0$ (resp. $F1$, $F2$, $F3$, $F4$) represents the probability that the estimated position is from 0 to $2m$ (resp. $2-4m$, $4-6m$, $6-8m$, $8-10m$) from the real position.

2.2 Security Zones

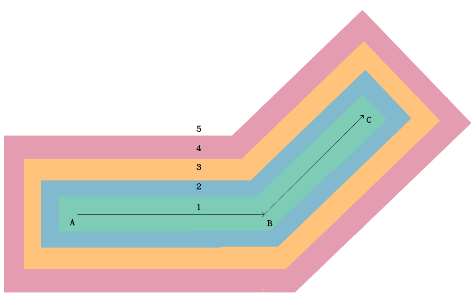

Fig. 2: Security zone

As explained earlier, we are interested in computing the probability of a drone deviating enough from its given flight plan in order to endanger the public. In agreement with software considerations in airborne systems and equipment certification (named DO-178C), we define 5 levels of security zones that are represented in Figure 2.

The size of each security zone is defined depending on the context of the flight plan. In our case, the size of the zones were fixed by PIXIEL, with the following semantics: no humans are allowed in Zones 1-3, while employees (resp. public) can only go to Zone $4-8m$ (resp. $50m$) from the intended trajectory. In this context, the probability of an accident involving humans is directly proportional to the probability of a drone entering Zones 4 or 5.

2.3 Formal Model

Our formal model is summarised in Figure 3. In this model, the position of the drone is computed as coordinates along the three axes. We assume that the drone starts from the origin and moves from point to point along its flight plan. One complete loop of the model corresponds to one period of the FC, i.e. position estimation using filtered data and computation of the next position according to the current deviation from the flight plan.

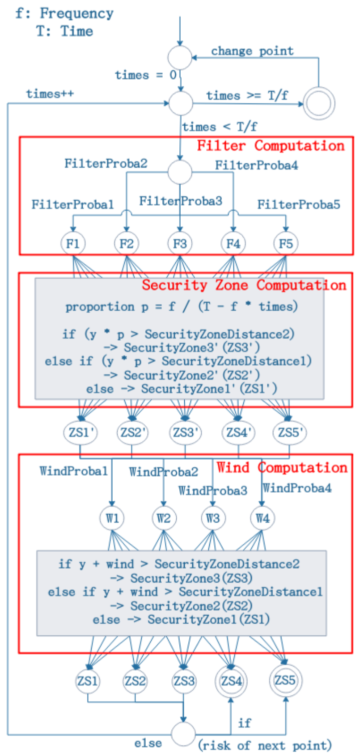

Fig. 3: Overall behaviour of the FCS

In addition, we also consider that wind can blow on the scene and deviate the drone. There are three stages in our model: Stage (1) takes into account the probability that estimated position is erroneous because of the inaccuracy of sensors and filters (parameters $F0, F1, F2, F3$ and $F4$). In Stage (2), we use the current estimated position to compute the intended next position of the drone (and the corresponding security zone), before wind perturbation. Finally, the wind is taken into account in Stage (3) and the effective next position is computed as well as the corresponding security zone. In our model, wind direction is constant but wind force is also parametric.

3 Parametric Statistical Model Checking

Our formal model is a parametric Markov Chain (pMC). Formal verification techniques for such models exist, but are complex and subject to state-space explosion. In practice, existing tools such as PRISM [7] and PARAM [5] can handle models with a few thousand states and a small number of parameters. Since the drone position is modelled using reals, and our model contains 10 parameters, it cannot be handled using standard model-checking methods.

We therefore use a technique called parametric statistical model checking in order to approximate this probability with formal guarantees. Like Statistical Model Checking [9] (SMC), pSMC uses random simulations in order to compute an approximation of the chosen probability. It allows to compute the probability of satisfying a given (linear) property as well as the associated confidence interval as polynomial functions of the parameters. The details of this technique are explained in [1].

4 Experimentation and Results

We have implemented our technique in a prototype tool that takes as an input a pMC encoded in a python program, which allows in particular to use real variables in order to encode the position of the drone. Using this tool, we were able to compute the parametric probability of the drone entering Zones 4 or 5 on a flight plan reduced to a straight line. Further experiments have been able to handle more complex flight plans but the results are not presented here.

application	wind	Z4-5 probability
application1	without	4.929%
application1	wind(56%,44%,0%,0%)	5.786%
application1	wind(50%,25%,15%,10%)	5.833%
application2	wind(56%,44%,0%,0%)	10.91%

Table 1: Results

While PRISM and PARAM run out of memory after a few hours of computation on a simplified model where wind is not taken into account, our prototype tool computes 20 000 simulations in about 3 minutes with our most complex model that includes wind parameters. The obtained parametric probabilities are unfortunately too complex to present in this paper, but Table 1 shows the evaluation of the obtained polynomials for precision parameter values obtained through practical experimentation and wind probabilities representative of the weather in Nantes, France. For this experiment, we have set the duration of the flight to 5 seconds, the frequency of the filter and position sensors to 4 Hz. For application1, precision parameters are set to 0.15, 0.3, 0.4, 0.1 and 0.05 respectively. For application2, precision parameters are set to 0.1, 0.25, 0.35, 0.2 and 0.1 respectively. The wind parameters correspond to the probability of having a wind force of $0-20km/h$, $20-30km/h$, $30-50km/h$ and $50-70km/h$ respectively.

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