Artificial Neural Network Based Automatic Emergency Landing Site Selection for UAVs and Highly Automated Aircraft

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Abstract—In this report an artificial neural network (ANN) based automated emergency landing site selection system for unmanned aerial vehicle (UAV) and general aviation (GA) is described. The system aims to increase safety of UAV operation by emulating pilot decision making in emergency landing scenarios using an ANN to select a safe landing site from available candidates. The strength of an ANN to model complex input relationships makes it a perfect system to handle the multi-criteria decision making (MCDM) process of emergency landing site selection. The ANN operates by identifying the more favorable of two landing sites when provided with an input vector derived from both landing site's parameters, the aircraft's current state and wind measurements. The system consists of a feedforward ANN, a pre-processor class which produces ANN input vectors and a class in charge of creating a ranking of landing site candidates using the ANN. The system was successfully implemented in C++ using the FANN C++ library and ROS. Results obtained from ANN training and simulations using randomly generated landing sites by a site detection simulator data verify the feasibility of an ANN based automated emergency landing site selection system.

Keywords—Artificial neural network; emergency landing; unmanned aerial vehicle;

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have become widespread in the military sector and their proliferation is seeing an increase. The increased popularity has caused a decrease in the costs associated with UAVs and driven public interest. Civilian applications for UAVs are the subject of widespread research and development worldwide and regulatory entities are establishing legislation and guidelines for their use in a civilian context [1,2]. Operating UASs above populated areas is required for most of the feasible civilian applications however this brings serious risks if accidents occur as these could result not only in hardware loss but also harm to civilians. This highlights the need for reliable automated emergency landing systems for UAVs. The use of parachutes for a controlled descent in case of emergencies has proven the more popular concept so far however it lacks control and is highly susceptible to atmospheric conditions [3]. If a UAV was to suffer failure above a populated area, resorting to a parachute could result in catastrophic consequences if for example the aircraft touches down on a highway or collides with a pedestrian. Therefore this type of emergency landing system is not adequate in its current state for use over populated areas.

Our approach is based on the premise that the UAV still possesses some degree of flight control so that the aircraft is able to maneuver to a desired landing site. This report focuses on the automation of the emergency landing site selection aspect of the problem. More specifically, selecting the most favorable landing site in terms of hardware survivability and safety to the public within gliding distance of the UAV. The lessons learnt from this work should benefit future work in this area and become a basis for part of an automated emergency landing module for UAVs. Developing such a technology could even propagate back into general aviation (GA) as an aid for pilots in case of an emergency landing, to suggest them favorable emergency landing sites.

This report is structured as follows. Section II further investigates existing work. Section III describes the methodology which led to a working system Section IV Outlines the case studies performed and results obtained Section V describes conclusions drawn from the findings and possible future work on the topic.

II. BACKGROUND AND RELATED WORK

A. Automated Emergency Landing Site Selection for UAVs

The automated emergency landing problem can be broken down into three parts; landing sites detection, landing site selection and guidance for the landing itself. For the scope of this report, emergency landing scenarios assume the aircraft retains functional flight controls. Therefore guidance is dealt with using a conventional auto-pilot using optimal gliding targets. There is no conventional method however for automated landing site detection and selection. Limited literature exists on emergency landing site detection and is largely summed up here [4,5,6]. Landing site election however remains largely undocumented as it is highly dependent on site detection which is not an established field. It serves to reason that one must appropriately detect candidates before a selection can be made. The system developed can be used when possible emergency landing sites as the aircraft flies and characterizes major physical aspects of each. Detected landing sites are limited to reasonably flat areas large enough for the aircraft to land safely in. Limits on allowable roughness and necessary area are dependent on the aircraft model.

Most literature tends to focus on finding any emergency landing site and flagging them as targets. To a human pilot, determining whether a landing site is favorable or not is a process largely driven by context. To the author’s knowledge no strict guidelines are maintained by regulatory bodies to assess the safety level of an emergency landing site in depth.
For a pilot facing an unpowered emergency landing situation, the site selection process is swift and often done with limited information.

Landing site selection for the final descent of spacecraft has proven to be the most closely related field with useful publications. Fuzzy logic based systems have been shown to be competent at estimating the desirability of a landing site [6]. However, fuzzy logic based systems become more difficult to design as the number of inputs considered increases and the decision process increases in complexity. This approach is dependent on creating a set of rules dictating an output based on the relationship between the inputs. As more inputs are considered, establishing the rules becomes harder as the relationships must be deduced from a pilot's decision making which is often based on contextual information which in turn is difficult to quantify.

B. Multi-Criteria Decision Making (MCDM) and MCDM Using Artificial Neural Networks

The use of multi-objective and MCDM for UAV has been an active field of research [8-16]. In order to identify further related publications let us assume the site selection problem is a multi-criteria decision making (MCDM) problem. The information provided by a detection system is formatted in a manner befitting of MCDM therefore published solutions to real-time MCDM problems are relevant to this project. Artificial Neural Networks (ANNs) have been shown to have the ability to mimic human MCDM capabilities in certain scenarios [18,19,20,21]. Therefore it stands to reason that an ANN through its training using samples consisting of input vectors and corresponding desired outputs emulates a set of rules unknown to the designer. This is ideal for emergency landing site selection as a pilot's decision making need not be understood and mapped but simply treated as a black box and sampled adequately.

III. METHODOLOGY

A. Decision Making Model

Two decision models were considered for the ANN's role in selecting the best landing site candidate. The first method involved the individual evaluation of each landing site and attributing them scores on a predetermined scale. The second method is the process of completing pairwise comparisons between candidates up to a point where a ranking can be established. Although the scoring method appears more efficient at first, it is difficult to implement due to the training sample generation process. In order to train a feedforward ANN through back propagation training samples which are consistent and accurate are necessary. When pilots were asked to perform both type of assessment for a few list of sites it was quickly identified that they had little to no basis in attributing a score as they do not possess a conceptual scale for it. When confronted by two landing sites however, the pilot’s decisions concerning which of the two is superior was consistent and the criteria affecting the decision could more easily be extracted through their feedback. For these reasons, the pairwise comparison decision model was identified as the most promising.

![Fig. 1. Possible decision models for ANN based site selection](image)

A binary search algorithm based system was implemented to handle the selection of necessary comparisons before a ranking can be established and to reduce the number of comparisons needed when adding new landing sites to an existing ranked list.

B. Artificial Neural Network Training

Experimentation with different training methods showed the Levenberg–Marquardt training method to be most effective. Training parameters were adjusted through trial and error until the desired performance was obtained. The generation of training samples however was key to improving the ANN’s performance. The implemented ANN has 12 inputs as is covered in the following subsection. The number of samples required to effectively cover the ANN’s entire operational envelope increases by a factor of $n$ at the very least for each new input; $n$ being the new input number. In order for the system to be feasible, the number of samples to train it adequately must be obtainable through pilot assessment of each sample. For the scope of this report pilot assessment was replaced with a simplified weighted sum to first identify if the system could replicate this behavior. This allowed the generation of the desired output for each sample to be done extremely quickly. The inputs for the samples were generated using input from a site detection simulator. This simulator is modeled after a prototype system currently under development and produces the same inputs in their expected ranges.

C. Picking the inputs

Perhaps the most critical part of a feedforward ANN performing a MCDM task is the selection of its inputs. In order for the decisions to be representative of the real world, the inputs must take into account as many details as is practical which influence the decision. When determining the safer of two landing sites, the influential characteristics are each site’s physical parameters such as roughness and slope angle, the aircraft’s position and the wind conditions. Site characterization is an involved process when performed from an aircraft flying at altitude at cruising speed. The system however is available and landing site profiles are available through it. Although all influential inputs must be used, they can be combined in various ways to reduce the overall number of input neurons in the ANN. For example instead of providing the slope angle for both sites individually, the difference between the two was selected as an input as this was identified as the manner in which slope angle was influencing the
The variables selected as inputs for the ANN are listed in Table I along with a short description for each.

<table>
<thead>
<tr>
<th>Input Name</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope Angle Difference</td>
<td>Uphill slows the aircraft.</td>
</tr>
<tr>
<td>Roughness Difference</td>
<td>Flat land eases the landing.</td>
</tr>
<tr>
<td>Roughness Confidence Difference</td>
<td>SDS’s confidence of roughness estimate</td>
</tr>
<tr>
<td>Angle Between Wind Direction and Principal Landing Site Axis Difference</td>
<td>Landing with headwind allows for slower landing speed.</td>
</tr>
<tr>
<td>Wind Speed</td>
<td>Directly affects the value of wind direction.</td>
</tr>
<tr>
<td>Distance To Site Difference</td>
<td>Closer landing sites tend to be safer to reach.</td>
</tr>
<tr>
<td>Number Of Obstacles Difference</td>
<td>Less obstacles is always safer.</td>
</tr>
<tr>
<td>Average Obstacle Clearance Difference</td>
<td>Further obstacles are always safer.</td>
</tr>
<tr>
<td>Nearest Obstacle Clearance Difference</td>
<td>Outlining close obstacles can be dangerous.</td>
</tr>
<tr>
<td>Site 1 Classification Number</td>
<td>Represents “water,” “forest” etc.</td>
</tr>
<tr>
<td>Site 2 Classification Number</td>
<td>Represents “water,” “forest” etc.</td>
</tr>
<tr>
<td>Size Difference</td>
<td>Larger landing sites give more room for error.</td>
</tr>
</tbody>
</table>

IV. SIMULATIONS AND RESULTS

The training of the ANN was done using only 70% of the 10,000 samples generated. The other 30% were used for validation and testing. After multiple attempts, performance peaked at 91.2% of correct decisions. Correct meaning the desired output as calculated using the place holder estimation function matched the ANN’s output.

This ANN was incorporated into a framework coupled with the site detection simulator and an aircraft flight path data player to determine whether keeping a ranked landing sites list up to date using an ANN system performed. The percentage of correct decisions was slightly smaller after multiple hours of simulations it was established to be 86% as opposed to the initially reported 91.2%. This is however still a high amount of accuracy considering the ranking process for a site typically involves 3 to 4 comparisons. Within this system, landing sites no longer within gliding range are also removed from the candidates list. Therefore erroneously placed landing sites only affect the ranking for a short period of time.

Fig. 2 below depicts a typical simulation output when viewed using the Rviz ROS package. The red line represents the aircraft’s flight path; the green outlines are the contours of each landing site with the red dots being their centroids. The blue rectangles represent obstacles whilst the blue arrows represent the principal axis, longest straight line, of the landing site. Below the Rviz output can be seen the landing sites ranked in decreasing order of desirability from top to bottom.

V. CONCLUSION

In this report a system was successfully implemented using an ANN to perform pairwise comparisons of landing sites and establish a ranking based on those comparison outcomes. Consequentially it was shown that ANNs can be adapted to solve landing site MCDM problem to a certain extent. However the ANN’s performance should be further optimised to reach a more desirable confidence in its decisions as 86% could lead to problematic results if used in a real scenario. The framework which was developed however has been shown to adequately communicate with the site detection simulator and handle the ranking of landing sites in real time.

Further work will involve refinement of the ANN training process and sample generation in addition to the replacement of the place holder desired output formula with pilot assessed training samples. A comparative study with a genetic algorithm implementation of AELSS is also foreseeable which will help reinforce the field.

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REFERENCES


