Predicting and Managing Multifactor Unknowns in Flight

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Problem

A critical flight situation is typically the result of spontaneous mixing and unfavorable cross-coupling of several risk factors in the 'pilot/automaton – aircraft – operating environment' system dynamics: adverse weather, pilot errors, automaton's logic flaws and mechanical failures. In spite of a negligibly small probability of occurrence, multifactor (off-normal, complex) flight situations do happen in operations, often leading aircraft to 'chain reaction' accidents (Fig. 1). The majority of multifactor scenarios are not known to pilots and engineers. The difficulty is 'the curse of dimensionality': too many cases are to be learnt in advance. At present, the volume and the quality of knowledge on multifactor flight domains (programmed in control automata and described in pilot manuals) may be insufficient.

Solution approach

In order to be avoided or safely resolved, a broad spectrum of potentially dangerous multifactor situations must be explored in advance and timely recognized onboard. A knowledge-centered solution approach to flight automation has been developed to address the problem of accident prediction and prevention in multifactor/ unknown situations. High-fidelity mathematical modeling, fast-time computer simulation, artificial intelligence, knowledge mining and mapping techniques should be harnessed earlier in the lifecycle. The goal is to fill the gaps on the complex situational tree in a pilot's (automaton's) knowledge base and help de-materialize dangerous multifactor flying experience from the outset (Fig. 2).

Technique

Using the system dynamics model as a virtual test and operation article, it is possible to screen potentially unsafe multifactor flight domains ('alternative futures') in advance. Large sets of realistic off-normal scenarios are automatically explored and analyzed for safety in the form of a situational tree (Fig. 3). Situational trees are used to retain information on potential anomalies in the system behavior, quantify critical combinations of risk factors, derive recovery options, and depict optimal and prohibited control sequences using 'a bird's eye view' knowledge maps (Fig. 4). The objective is to predict flight paths and implement safety protection tactics under complex/ uncertain conditions for 10…30 seconds ahead.

An artificial intelligence system (AI pilot) model has been developed for flight safety prediction and protection based on a self-preservation imperative. Its key components are: theory of multifactor flight domains, fast-time flight M&S techniques, knowledge mining and mapping techniques, low-cost large capacity memory, methods of guaranteed quick access to a knowledge base, and some other.

Major challenges

There are several challenges on the way of bringing flight safety protection AI onboard. These issues include: trust in safety AI, knowledge base competence measurement and comparison, control authority transfer rules, knowledge base verification, validation, accreditation and update for a fleet of vehicles.

Conclusion

An affordable memory-based AI safety protection automaton can be developed. The automaton should incorporate a comprehensive knowledge base on the system dynamics in multifactor situations (generated in advance in virtual fast-time flight M&S experiments), knowledge based what-if flight path prediction and vehicle self-preservation techniques. The knowledge base should have a tree-type structure with a guaranteed real-time access capability. Its volume can exceed the volume of multifactor (off-normal) flying experience accumulated by all pilots for all relevant aircraft types operated in the past.

References

http://aixtree.mcdir.ru/publ/18_Paper_SAE_2011-01-2659_manuscript_v-2.pdf.
http://aixtree.mcdir.ru/publ/15_ICAS_2010_723_updated.pdf.
http://aixtree.mcdir.ru/publ/AUVSI_USE_2007_v-2.pps
http://aixtree.mcdir.ru/publ/13_SICPRO_Paper_2009.pdf (in Russian).
http://aixtree.mcdir.ru/publ/04_SAE_1998_Paper_Number_981223.pdf.

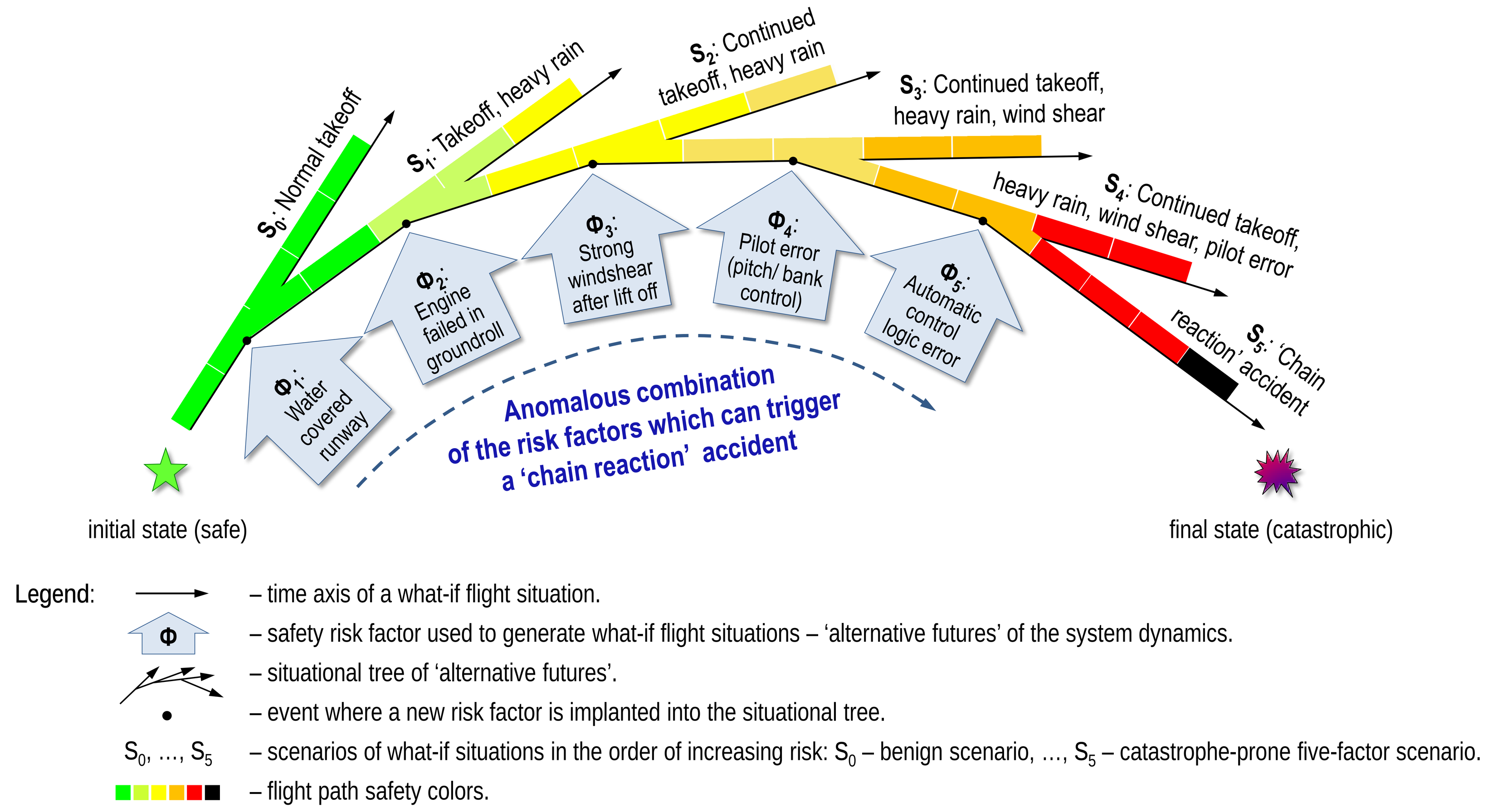
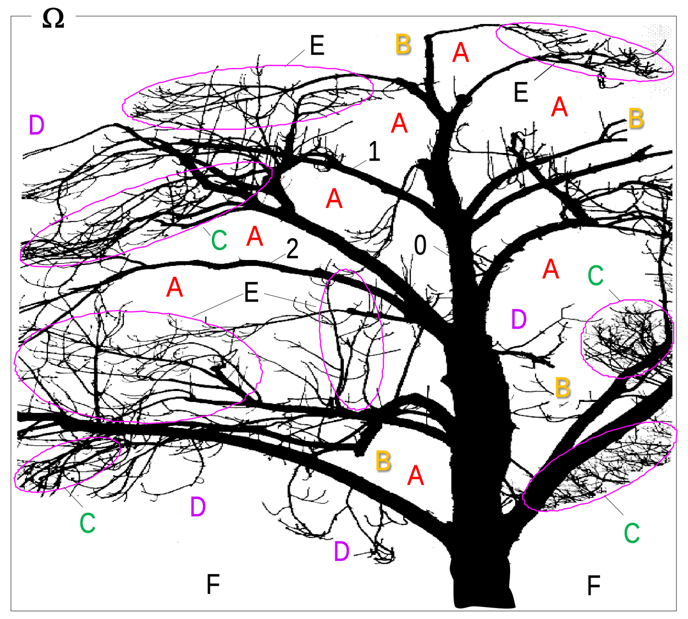


Fig. 1 – Build-up mechanism of multifactor flight situations – takeoff domain example

(a) major defects of a human pilot's tactical knowledge base

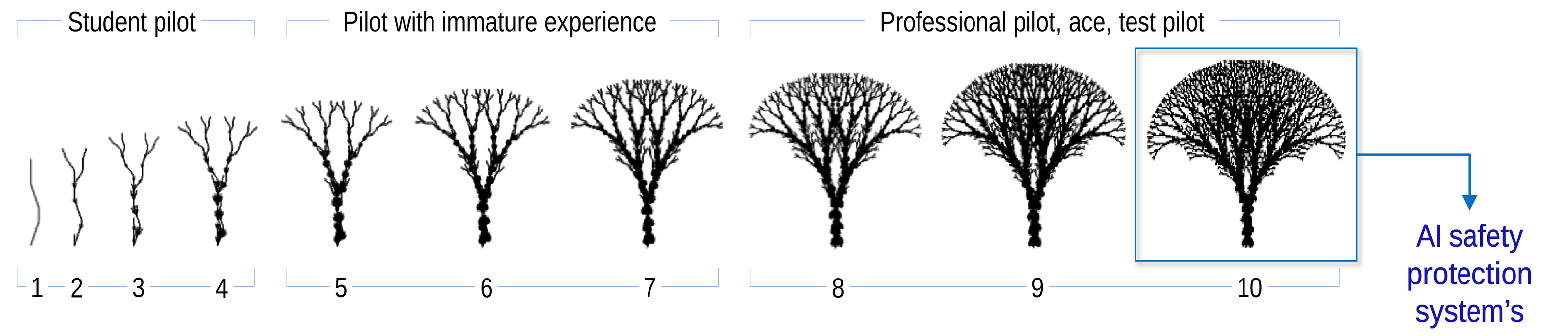


Legend:

Natural tree analogy:	Characteristic subsets of a human pilot's knowledge base:
Ω Tree growth space	⇒ Space of possible scenarios.
0 Tree's trunk	⇒ Baseline scenario.
1 1st-order derivative branch	⇒ One-factor off-normal scenario.
2 2nd-order derivative branch	⇒ Two-factor off-normal scenario.
A Absent but possible branching	⇒ Missing knowledge.
B Dry or broken branches	⇒ Forgotten/ shadowed knowledge.
C Excessive, chaotic branching	⇒ Non-systematic knowledge.
D Insufficient, sparse branching	⇒ Fragmentary knowledge.
E Optimally dense branching	⇒ Systematic, sufficient knowledge.
F Region impossible for branching	⇒ Unattainable scenarios.

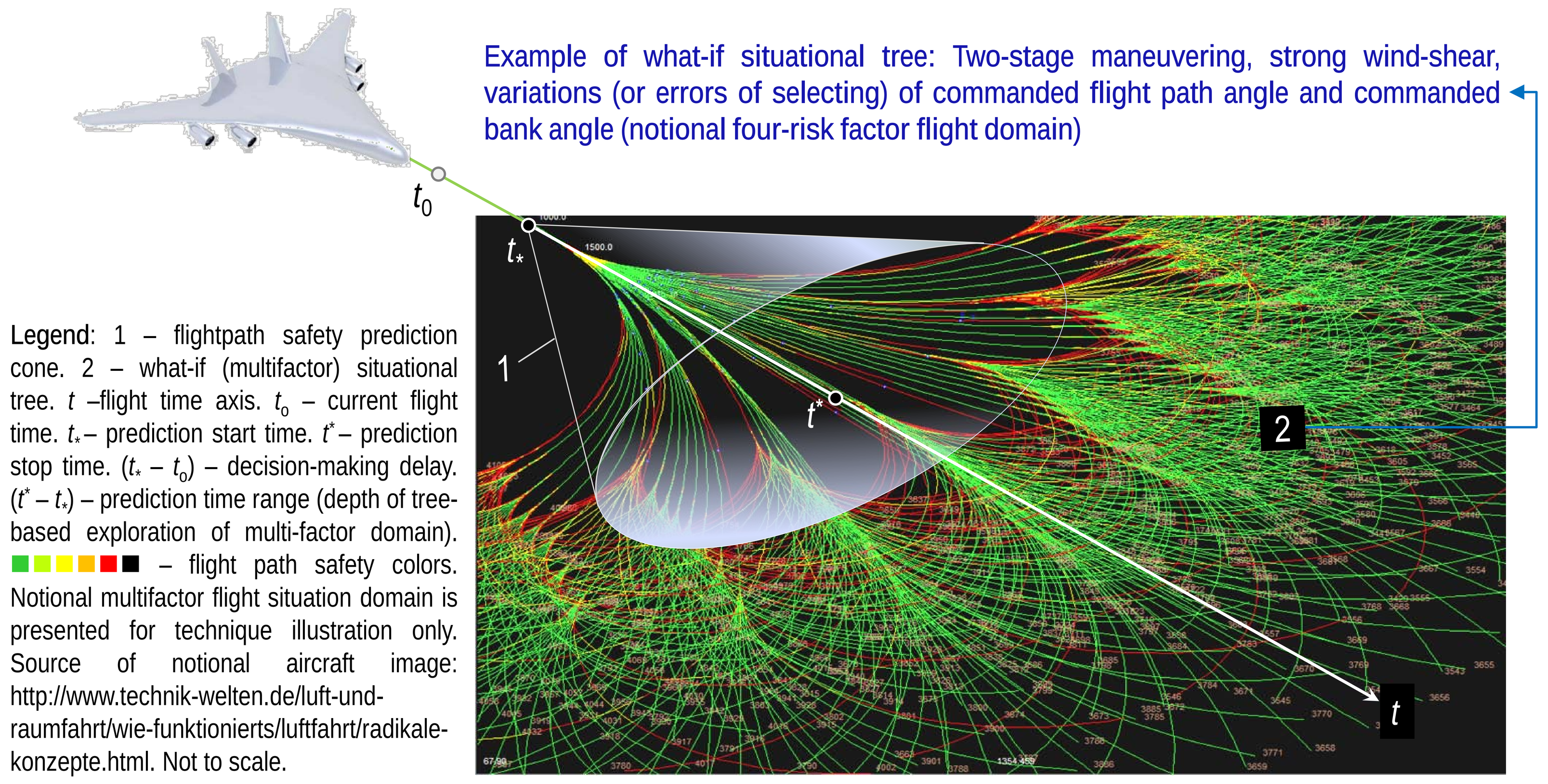
Major defects of a human pilot's knowledge to be backed up by flight safety protection artificial intelligence (AI)

(b) fractal tree growth as a model of an ideal human pilot's (AI's) situational knowledge base development in memory



Legend: 1,2, ..., 10 – the maturity levels of a human pilot's experience in addressing multifactor flight situations.

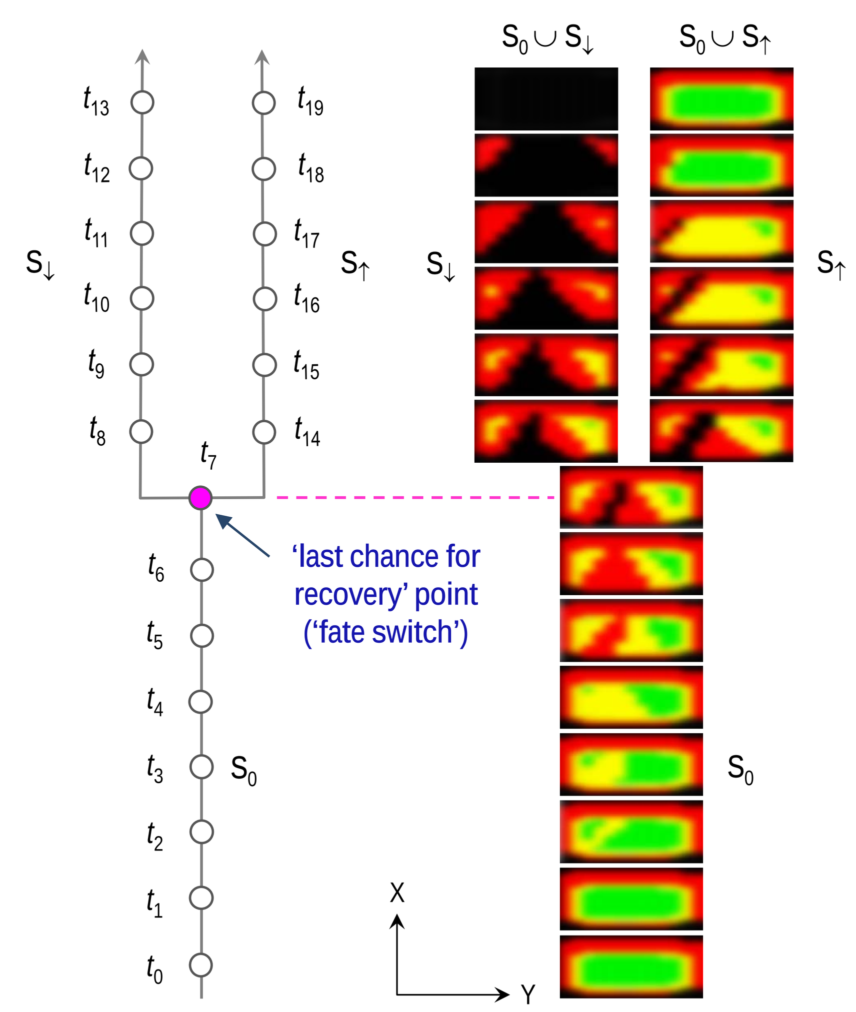
Fig. 2 – Bad and good structures of a knowledge base on multifactor flight situations



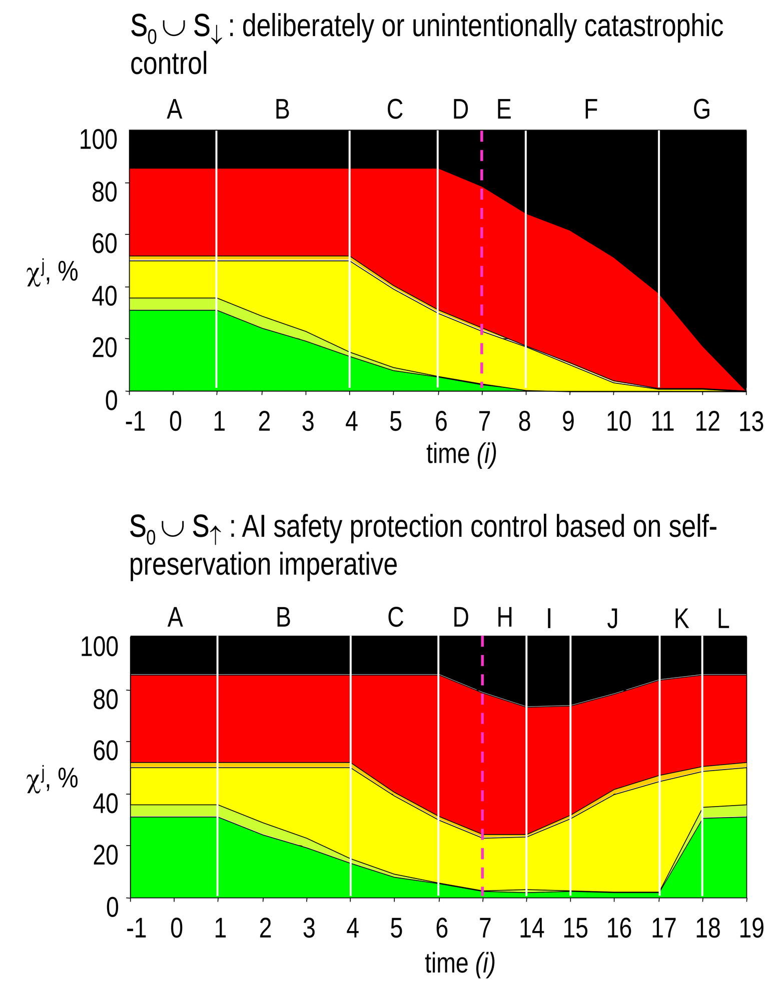
Legend: 1 – flightpath safety prediction cone. 2 – what-if (multifactor) situational tree. t – flight time axis. t_0 – current flight time. t_* – prediction start time. t' – prediction stop time. (t_* – t_0) – decision-making delay. (t' – t_*) – prediction time range (depth of tree-based exploration of multi-factor domain). – flight path safety colors. Notional multifactor flight situation domain is presented for technique illustration only. Source of notional aircraft image: http://www.technik-welten.de/luft-und-raumfahrt/wie-funktionierts/luftfahrt/radikale-konzepte.html. Not to scale.

Fig. 3 – Real-time flight path safety prediction in multifactor/ unknown conditions using situational trees

(a) time-history tree of safety windows



(b) safety chances distribution time-histories



Legend: Scenario segments: S_0 – obstacle approach, $S_\downarrow$ – imminent collision, $S_\uparrow$ – collision avoidance. $S_0 \cup S_\downarrow$ – deliberately or unintentionally catastrophic flight control tactics). $S_0 \cup S_\uparrow$ – AI safety protection system flight control tactics based on self-preservation imperative. Safety window's axes: X – commanded flightpath angle. Y – commanded bank angle. Scenario segment's time lines: $\{t_0, t_1, ..., t_7\}$ – S_0, $\{t_8, ..., t_{13}\}$ – $S_\downarrow$, $\{t_{14}, ..., t_{19}\}$ – $S_\uparrow$. Key time instants: t_7 – 'last chance for recovery', t_{13} – 'just before impact', t_{19} – 'safety restoration complete'. A, B, ..., L - characteristic states of the aircraft safety dynamics. χ^j – flight safety chances at ξ^j level, j∈{I, II-a, II-b, III, IV, V}, ξ^j ∈{■■■■■■}. t_i – time instants, i∈{-1, 0, 1, ..., 13} ∨ i∈{-1, 0, 1, ..., 7, 14, 15, ..., 19}.

Fig. 4 – Knowledge maps for representing catastrophic and recovery control tactics (flight in the presence of obstacles: model cases of 11.09.2001 and 24.03.2015 accidents)