Building Human Profile by Aggregation of Activities

Application to Aeronautics Safety

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Abstract. The work related here is devoted to the setup of a methodology regarding the study of polyvalent objects about which our knowledge is incomplete.

It is concerned with the analysis and characterization of flights/flight maneuvers, considered from the standpoint of the involved human operators. The two following issues have been identified: 1) *incompleteness*, which comes from the second-hand nature of the recorded data that describes and situates the pilot's activity, and 2) *variability* of human sensations and reactions, as a result of which identical stimulations may cause different reactions and different observations may correspond to identical sensations/situations.

Our aim is not to close up on the theoretical mechanisms of perception and preference but, based on these mechanisms, to obtain a behavioural model that will be used 1) to characterize observed patterns amongst the various recorded data, 2) to anticipate the patterns to be observed and to relate them to particular flight conditions.

We introduce the three-step process of supervised aggregation, an aggregation driven by experts and expertise, which we successfully put into practice in the case of elementary turns. This process was developed aiming to convey characterizing and predictive power, notwithstanding the incompleteness and variability of observable data.

1 Framework of the Study

> From the sets of recorded parameters during these 10 flights, could you come up with a "*mean*" flight ? (Captain D., Mirage squadron — March 22nd, 2005)

The above is a straightforward statement of the goal pursued in the project Activity Modeling and Aggregation of Flight Profiles, 2008-2011. More precisely, by "*mean*" flight, we mean a *representative* flight, that will contain the important and distinctive features of the 10 original flights. This project, in which flights

M. Kurosu (Ed.): Human Centered Design, HCII 2011, LNCS 6776, pp. 389–396, 2011.

are considered according to displayed human activity, attempts a *descriptive* rather than *evaluative* approach.

Because flights, and hence flight recordings, are complex objects, the latter consisting of several figures related to each other in various ways, one cannot generate an aggregate description by simply averaging the data recorded during each individual flight: this data has to be preliminary processed into figures and modes relevantly suited to feed some aggregation procedures.

In this project, we consider flights (the studied objects) from the standpoint of the human activity (mainly that of the pilot, but possibly also that of other crew members and operators), which it originates from. In the analysis that follows, it is essential not to jumble up the data used to depict the piloting activity and this activity itself.

1.1 Issues

While configuring the Supervised Aggregation Process (SAP), we acknowledged the need to reckon with the two important issues examined below.

Incompleteness: The first issue is the incomplete nature of any description, which can either be due to lack of information (some meaningful parameters, such as speed or outdoor temperature, have not been recorded) or to an important parameter being implicitly contained in the recorded data. The first shortcoming cannot be avoided and one must keep constantly aware that meaningful data may be lacking or incomplete. There are two ways to deal with the second shortcoming: 1) first, any implicit parameter can be explicitly added to the description of a flight, 2) second, the aggregation procedure can be selected so as to keep invariant the important parameter. To the benefit of the latter solution, it doesn't require the user to modify the objects to aggregate.

Variability: Concerning processes involving human beings (or more generally living beings), an additional reason for keeping the distinction between the studied objects and the characters signifying them is the variability of the reactions of living organisms.

In [3], Chevallard relates such variability to the learning process, during which knowledge stems from a progressive unification of different representations.

1.2 A Main Tool: Probabilities

The first and one of the main tools developed for the description of polyvalent states and characters, is the science of probabilities. A probability is a real number between 0 and 1 attached to any state of the investigated system, that can be considered as standing for the "*chance*" for this state to be observed.

Next, one is led to consider different kinds of probabilities, as already advocated by the French economist Augustin Cournot (1801-1877). A descriptive probability, used to depict polyvalent states, is somewhat different from a probability describing ignorance or from one used to depict "*randomness*" (for an introduction to the connections between randomness and ignorance, see [4]).

Lastly, probabilities may also be used to shade the overly precise descriptions of an uncertain phenomenon that numbers are bound to provide. To this end, several models of imprecise probabilities (Dempster-Shaffer Model, Transferable Belief Model, Capacity Model... see [5] for an overall introduction) have been developed.

To sum up this brief review on probabilities, it appeared to us that they don't possess the precision and univocity that is usually attached to figures, and that seems necessary in order to aggregate a set of objects into an object of the *same kind*. Indeed, in order to achieve this goal, certain choices have to be made that cannot be made without some kind of *meta*-knowledge on the situation. For instance, in order to specify an average speed for a set of maneuvers in which these average speeds are regularly spaced, rather than selecting any specific numeric mean, it might be observed that these speeds all are functionnally related to (a combination of) some other recorded data, such as aircraft's weight and visibility conditions.

Hence, we realize that the outcome of the aggregation of a set of complex objects (to which flights certainly belong) can't end up in a similar object (another "*mean*" flight), but will result in a set of (functionnal) relations concerning the characters describing the objects, and shared by the latter (a set of *common features*).

Cournot's standpoint over probabilities, highly original for the time, has nowadays attained overall acknowledgement, as can be seen in Barberà's work hereinafter cited.

2 The Supervised Aggregation Process

2.1 Definition

We offer to carry on the three-step SAP, which we developed as an extension of Barberà's preference aggregation process [1]:

1) **decomposition**
2) **maieutics**
3) **reconstruction**

Here, "*supervised*" means that, at each step, the constraints will be set up by expertise: *e.g.* the number and type of characteristics (in the decomposition step), the number of expected rules (maieutic step), as well as the selection and combination of these rules (reconstruction step).

As in Barberà's process, the first step, <u>decomposition</u>, consists in expressing the studied objects using a convenient (from the expert point of view) set of decomposition characters.

It's in the second step, <u>maieutics</u>, that our SAP differs: in Barberà's aggregation process, this step consists in "applying mean operations" to each (or some) of the decomposition character, to end up with similar characters. However, as we indicated above and established earlier in [6], the outcome of the second step should be a meta-object rather than a mere set of means, which would be similar to the characteristics resulting from the first step.

> In other words the aggregation of a set of items should lead to a higher-order object that would signify the essential properties shared within the studied set: the aggregation of activities should end up in a "*way of doing*", the aggregation of flight data files should consist in a set of rules defining the piloting properties shared by these flights.

The last step of the aggregation process, reconstruction, consists in a relevant use of the several rules and relations that sprang out of the maieutic step: *i.e.* an inference engine, or a sequence of rules defining the sought procedure.

Thus, the SAP allows the design of *specific ways for doing things*, from a set of actual exemplary activities. In the sequel, a static version of the SAP is summarized, before a version of the full dynamic process is introduced.

2.2 Static Aggregation Based on Galois Lattice Induction

In [2], we introduced the Galois Lattice Induction formalism for describing the complete aggregation process of the stimulus/response database generated by a human subject. Such a process enables the construction of a "*mean*" human activity profile, that we call the "*Virtual Subject*".

Because only the "*stimulus–response*" transition is aggregated, this aggregation is said *static*. Its three phases are: 1) decomposition: each stimulus and each response is signified by a vector of characteristics. The set of responses given by the subjects S, each submitted to every stimulus of the set of stimuli St, consitutes the experimental database E, 2) maieutics: this stage consists in running an "*association rule process*" (a non-supervised rule-induction method) on the database E. A subset of rules, $\Lambda' \subset \Lambda$, whose premises are the properties of the stimulus and whose conclusions are the obtained responses, are then filtered according to the values of their confidence and portance. The output of the maieutic step is a knowledge-base K, *i.e.* a set of rules relating properties of the environment to observed responses, together with the related subsidiary information (particular cases, portance and confidence...), 3) reconstruction: a classical inference engine runs on K so as to simulate an "*aggregated subject*".

Formal model for the Static Agregation: let us consider a set of subjects $\mathrm{S} = \{\mathrm{S}_n\}$, $n \in [1, N]$ that are asked to evaluate a given corpus of phenomena. Each phenomenon is being described through a spectrum of parameters $\mathrm{P} = \{\mathrm{p}_i\}$, $i \in [1, I]$. The phenomena database is a corpus of events $\mathrm{E} = \{\mathrm{E}_m\}$, $m \in [1, M]$ (eg: a set of aircraft sounds). Naturally, each E_m is decomposed on the spectrum of parameters $\mathrm{P} : \mathrm{E}_m \rightarrow (\mathrm{p}_{m,1}, \ldots, \mathrm{p}_{m,i}, \ldots, \mathrm{p}_{m,I})$. The evaluations/reactions of the subjects are measured by a set of evaluation characteristics, $\mathrm{V} = \{\mathrm{V}_j\}$, $j \in [1, J]$.

The outcome of such an experiment is a set of items defined as follows: given one subject S_n and one event E_m, the final results of the subject's evaluation is the vector

$$\left(\mathrm{v}_{(n,m,1)}, \mathrm{v}_{(n,m,2)}, \ldots, \mathrm{v}_{(n,m,j)}, \ldots, \mathrm{v}_{(n,m,J)}\right) .$$

Using the corpus correspondence between the events and their parameters, it is easy to consider that the experiment is a relational database of $N \times M$ items: *(event, subject, event description parameters, subject's evaluations).*

Formally this *"Experimental Database"* is a set of identifiers *event* $\times$ *subject*, say ES, bearing out a list of values :

$$\left(\mathrm{ES}_{m,n}, \{\mathrm{p}_{m,1}, \ldots, \mathrm{p}_{m,i}, \ldots, \mathrm{p}_{m,I}, \mathrm{v}_{(n,m,1)}, \mathrm{v}_{(n,m,2)}, \ldots, \mathrm{v}_{(n,m,j)}, \ldots, \mathrm{v}_{(n,m,J)}\right) .$$

Association rules. Such a database is a natural candidate to be analysed by Galois Lattice theory.

Indeed a large body of literature about *"association rules"* supported by Galois Lattices exists. This theory allows to generate a rule database Λ^* containing all the rules of the template: *(rule identifier, confidence, portance, conclusion, list of premises).* The confidence c is defined as the proportion of *event* $\times$ *subject* that verify the rule among those that verify all the premises in the *"Experimental DataBase"* (conversely, $1 - c$ is the proportion of counter-examples). The portance, p, is the proportion of such events, though this time taken amongst the whole database (thus $0 < p < c < 1$). Many algorithms exist so as to extensively unearth these rules (and generally considering only those for which $0.5 < c$).

The *"association rules"* approach is known to be the most generic non-supervised rule induction method.

Λ^* is defined as the knowledge-base resulting from the aggregation process (to the c and p thresholds) of the responses given by the subjects $\mathrm{S} = \{\mathrm{S}_n\},\ n \in [1, N]$ to the events $\mathrm{E} = \{\mathrm{E}_m\},\ m \in [1, M]$.

The Virtual Subject. The final step is to define the *"Virtual Subject"*: a classical theorem prover can run on this Λ^* knowledge-base, so as to define a new functional relation between any new event e (qualified by the list of values of its I parameters) and the derived evaluation values $\mathrm{V}_e = (\mathrm{v}_i)_{i \in [1,J]}$ proved by the prover ran on Λ^*. We use the fact that each characteristic v_i of the obtained evaluation can then be proved following different proof-chainings to quantify and qualify the rules, with the use of three figures: c_m is the mean confidence, p_m the mean portance (both are quite classical), and pp is the **proof-power** of v_i, *i.e.* the number of proof-chains that result in v_i.

The first application of this induction/deduction loop has been made so as to define a *"Virtual Resident"* (*i.e.* the aggregation of 320 subjects submitted to 100 aircraft sounds). The induction/deduction is programmed in constrained Prolog (*i.e.* also: self-proved programs).

The Static Aggregation methodology is currently studied for application to various kinds of human driven activities, leading to the characterization of interfaces, or to the establishment counciousness characteristics in UAV (Unmaned Aircraft Vehicles) piloting, among others.

However, Galois Lattices are not suitable for cathcing dynamic activities such as the piloting activity itself, for which variational approaches must be used. The purpose of the next section is to sketch out such approaches.

2.3 Supervised Aggregation of Flights: From FDR to Flight Profiles

The first corpus that we used is a set of tactical simulated flights (helicopters) demonstrating a right-or-left turn engaged so as to avoid an obstacle. The second corpus is a set of 20 commercial aircraft flights on which the SAP is blind-tested, as what has to be discovered remains unknown, except from the dates of certain key points.

Here the SAP for flight profiles is developed through a Lagrangian variational methodology: a given flight is decomposed through a set of 83 flight parameters, including time, thus enabling us to consider it as being a trajectory in a state space. The details of the software development for the methodology, that we have implemented in Java, will not be developed in this paper.

The maieutic step consists in considering an N-tuple of pivotal key points given by expertise, $(\mathtt{Kp}_1, \mathtt{Kp}_2 \ldots)$.

Table 1. Expertise format

Flight	dates			
	Key Point 1	Key Point 2	Key Point 3	...
Flight 1	$\mathtt{Kp}_1^1$	$\mathtt{Kp}_2^1$	$\mathtt{Kp}_3^1$	...
Flight 2	$\mathtt{Kp}_1^2$	$\mathtt{Kp}_2^2$	$\mathtt{Kp}_3^2$	...
...	...	...	...	...

Learning process: selection of the best rule accounting for a keypoint

Description of the learning process. The variationnal method that we implemented consisted in assuming that the observed key points matched the variation (increase or decrease) of some parameter: for each of the 82 parameters (the 83 recorded parameters minus TIME) and for each of the 6 keypoints, we computed the thresholds (`cTh` and `sTh`) of the rules of increase and decrease for this parameter, that would account for this keypoint.

The rule best describing "*when and where things are changing in a relevant way*" could then be selected and used to identify the example maneuvers on new flights.

For the first corpus, the rules generated by the SAP are consistent with what was expected from knowledge of flights-mechanics: indeed, the primary effect of a turn is the increase of the aircraft's banking attitude.

The second corpus, that we used more thoroughly, led to the following findings:

– If we obtain several possible rules reporting for the first keypoint, and a bit less for the second, we hardly get any for further keypoints, and none for the last. Moreover, using the thus-obtained rules to find out the latest keypoints appeared hopeless.

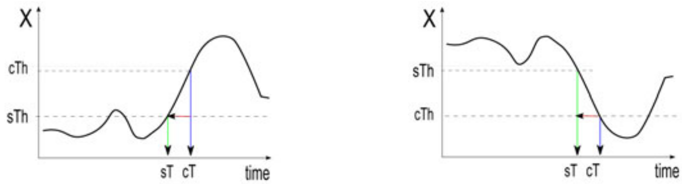

Fig. 1. Identifying the increase and the decrease of a measured parameter, X

- Concerning the first key point (the take-off), the best-evaluated rules were, in order, increases of the lateral wind, the banking attitude, and of two altitude parameters. Among these, only the first is not relevant to a physical phenomenon but due to the fact that the measure of the lateral wind started from the time the airplane's undercarriage had left the ground.
- As for the second keypoint (retraction of the landing gear), the two selected rule were an increase of altitude (which the expert dismissed, as it was due to the coincidence that the landing was retracted at roughly the same heights by the different pilots) and a decrease of incidence (which was validated by the expert as being due to a physical phenomenon related to the studied maneuver).

Further developments. Notwithstanding the fact that the two rules studied are quite simple, they also are basic, meaning that a huge variety of more complicated rules can be obtained from these two rules by suitable combinations.

In order to make our rule-production process more robust and wider-ranged, it therefore appeared important to:

1. implement the possibility of restricting the time-windows when a rule is looked for or is applied,
2. use expert-knowledge to discard some rules (during the phase of rule-identification),
3. develop a wider set of rules, in particular rules to be applied to discrete (non-numeric) parameters,
4. setup a way of combining several elementary rules, over different parameters, to have a complete set of complex rules at our disposal

The reconstruction step. that is currrently being processed, relies on expertise in order to provide results.

3 Conclusion

In this paper we described the main components of a Supervised Aggregation Process (SAP), philosophically grounded on the mathematical tool of probabilities, whose modern acceptation is issued of Cournot's work on the aggregation concept. The SAP model here depicted is an extension of the economical formalism developed by Salvador Barberà in the form of a three-step process: 1) decomposition, 2) maieutics, 3) reconstruction.

The touchstone of the SAP is the production, from a set of elementary measures, of a meta-object, *the rule* that constitutes the structure of the studied field. Its use for the study of human activity has been described, its main application being the semi-automatic aggregation of exemplary flights in a procedure defining them. Java programs are currently under development so as to achieve more relevant results. The application to new flight safety domains is expected soon.

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