Data combination using belief theory to assess driver's vigilance

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Abstract *Human error has been implicated as a causative factor in 85% of drivers' and operators' crashes, and lack of vigilance has been identified as the single most important factor in incidents involving human error. Driver vigilance could decline with sleepiness, fatigue or monotony. In Queensland, inattention and fatigue respectively contribute to 27% and 5% of reported crashes. Vigilance decline is characterised by an increased or absence of response to critical events. The current technology to assess and prevent vigilance decline is based on the isolate use of a particular device such as eye tracker or steering wheel movements. The reliability of these devices is debatable as the value of the readings could be highly inaccurate, uncertain, partial, conflictual or unreliable. Furthermore, there has been very little research examining the use of multiple devices to diagnose vigilance decline.*

The aim of this paper is to use belief theory to assess driver's vigilance. Belief theory is a formal tool suitable for representing the inaccuracy, uncertainty and asynchnocity of knowledge. Our approach consists of merging a set of measurements, related to the environment, driver, and vehicle, gathered from different Advanced Driver Assistance Systems (ADAS). This paper presents the theoretical basis leading to the development of an advanced in-vehicle system capable of assessing vigilance decline. The development of such a tool has a potential to be a major contributor to reducing death and injury rates due hypovigilance related driver's errors. [1]

1 Introduction

Various types of ADAS have been used to assess particular aspects of driving [Rakotonirainy 03]. ADAS exploit information from the environment, driver or vehicle to assist the driver. Environment based ADAS can detect road objects in the environments such as road signs, lane markings, pedestrians or distance to a car ahead [Labayrade 04a] [Labayrade 04b] [Ieng 05]. Vehicle based ADAS such as data logger gather information about vehicle dynamics. Driver based ADAS measure driver's motor movement (eg. head movement, eye blinks, eye gaze or steering grips) and physiology (*e.g.* heart rate, EEG, ECG) [Ji 02].

New ADAS research efforts integrate information from different sources such as lane marking detection with the driver's gaze [Apostoloff 04]. Such a system is capable of giving an indication of the driver's attention by assessing eye gaze, whilst taking into account the curvature of the road. Existing ADAS are only able to give a partial picture of driving behaviour, and can be prohibitively expensive. Currently there is no system that comprehensively integrates vehicle dynamics, driver psychomotor and environmental information to assess drivers' vigilance.

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The aim of this research is to prevent vigilance related crashes characterised by road or lane departure. Our prevention is based on an accurate prediction of driver behaviour. We fuse and analyse information related to the vehicle, the environment, and the driver, to represent an accurate description of driving situation [Rakotonirainy 05] [Gruyer 05].We integrate the analysis of the driver's behaviour, vehicle dynamics and environmental conditions (road and obstacle) to assess driver's vigilance level. The assessment method uses belief theory. Information about driver's vigilance and driving situation allows us to increase the accuracy of behavioural prediction (*e.g.* likelihood of lane departure). Future situations exhibiting risky behaviours are identified and appropriate interventions are chosen. Due to lack of space, this paper will not address intervention strategies.

2 Related works

Vigilance is: "*the working process which manages, adjusts and sustains the information processing activity* (*i.e.* the attention)" needed to perform any task.

Despite the availability of advanced physiological and advanced technology, driver's vigilance is still difficult to assess accurately in a driving situation. Different approaches have been used to assess driver's vigilance [Bekiaris 01]. As the driving situation is rich in information, most of those studies differ in the data they exploit, and in the way they collect it. This section surveys existing driving monitoring approaches.

2.1 Single device approach

2.1.1 Driver oriented approach

Face oriented [Din 98] systems use PERCLOS, occulomotor activities, eyelid movements, eye blinks, pupil diameter, gaze and head movements [Smith 03], and facial expression [Zhu 04] with yawn detection to assess fatigue. Endogenous indicators such as sleep quality, boredom or extraversion are known as factor that impact on driver fatigue and vigilance [Fletcher 05]. Physiological indicators such as polysomnographie, electroencephalogram (EEG), electrooculogram (EOG) and the electromyogramme have been used to assess vigilance and drowsiness [Khardi 92], [Steele 04]. However physiological devices are too intrusive and do not take into account individual differences [Thiffault 03b]. As such, they cannot be isolately used as a reliable source of information to build in-vehicle vigilance detection system, but they can be useful as validation tools.

Self evaluation method for somnolence and vigilance can give *a posteriori* assessment of the vigilance level. Unfortunately subjective methods can't be used as real time safety critical system; however they can be used as an index to evaluate vigilance detection systems.

2.1.2 Vehicle dynamic oriented approach

Vehicle dynamics can give information about the psychomotor behaviour of the driver. Thus, indicators such as standard deviation of steering wheel movement (SDSWM) [Thiffault 03]; lateral position (SDLP) [De Waard 96]; time to line crossing (TLC) [Batavia 00]; following distance or mirror checking [De Waard 96] [Nuria 00] have been used to assess driver performance. As we will see later in section 3.1 driver performances can be linked to driver state and to his vigilance level.

2.1.3 Environmental perception oriented approach

Endogenous factors such as circadian rhythm or lack of sleep are not sufficient for a robust assessment of driver fatigue. In [Zhu 04], Qiang-ji used environmental information such as time of the day, temperature, luminosity, humidity and traffic volume to assess driver's probability to be fatigued. Characteristics of driving task and driving scene such as repetitiveness, sameness could also affect driver fatigue [Thiffault 03] [Matthews 02]. In

[Fletcher 05], Fletcher proposed methods to assess the characteristics of driving scene to detect driver's monotony.

2.2 Multiple device approach

To our knowledge, there are insufficient researches which jointly use cues from the environment, vehicle and driver to assess driver vigilance. Bayesian Network (BN) approach has been used in [Nuria 00] to combine information related to the environment and driver behaviour in order to recognize and predict non impaired driver behaviour. Zhu *et al.* fuses and analyses environmental and endogenous data related to eyelid movement, gaze movement, head movement, facial expression, weather, and temperature and cabin noise to assess driver's vigilance [Zhu 04]. Although the aim of our research is similar, their approach is based on BN as opposed to ours which is based on belief theory.

2.3 Summary

In order to be used in a road safety system and to be efficient, vigilance detection monitoring system need to be robust. Unfortunately, none of the existing approaches offers a satisfactory integrated solution. Existing single devices show deficiency when they are deployed into real driving situations. The limitation of the data set for representing a situation featuring environmental, vehicles and driver information is a critical aspect of the robustness and the reliability of a driving assistance system. The more information that is exploited the more accurate and robust the result is, provided that the fusion and analysis mechanisms are sound. Recent research trends are gearing towards multiple devices approach.

3 Our approach

3.1 Vigilance assessment

Existing approaches do not enable a direct assessment of driver vigilance (see section 2). Instead, they give information about a specific state of the driver which can be related to fatigue, vigilance, monotony, cognitive load, drowsiness or a combination of those. Attempts to disentangle the relationship between these states are still in their infancy, but [Sagberg 04] [Zhu 04] [Rakotonirainy 03] already propose relational graph between them.

3.2 Merging information using belief theory

We gather data from different sources via different type of sensors exhibiting different levels of reliability. Therefore our data are heterogeneous, homogeneous, asynchronous, inaccurate and uncertain. The challenge is how to model and combine all these data in order to obtain a more reliable result. Belief theory is the most appropriate theory to address such constraints as it allows information gathered from different sources to be fused to infer results with some degree of certainty. Concretely, each device we use (*e.g.* eye tracker) gives partial information on driver vigilance. An observer will associate a reliability coefficient to each device. The coefficients correspond to how the observer believes data from a device are reliable. The belief theory will formally represent and manage the reliability from different sources.

4. The belief theory for the management of uncertainty in data combination problem

4.1 Belief theory

Belief theory, proposed by Shafer [Shafer 76], allows both to model and to use uncertain and inaccurate data, as well as qualitative and quantitative data. This theory is well known to «*take into account what remains unknown and represents perfectly what is already known*». This theory allows solving an association problem which consists of matching a state X among a set of known states $\{Y_1, Y_2 \ldots Y_n\}$. This generates a set of exclusive hypothesis $\{H_1, H_2 \ldots H_n\}$ where H_i means «*X is associated with* Y_i». One of these hypotheses is supposed to be the solution. In this paper, we combine all the criteria representing a state X (for example the fatigue level) with a state Y_i (with the same criteria as X).

Belief theory allows the evaluation of the veracity of the propositions representing the matching of different states. These propositions can be simple or complex:
$P_1 = H_i$ = «*observed state X is known state* Y_i »
$P_2 = H_i \cup H_j$ = «*observed state X is known state* Y_i *or* Y_j ».

We define a magnitude which characterizes a proposition. The magnitude is the basic probabilistic mass $m_\Theta()$ defined on [0,1]. This mass is very close to the probabilistic mass with the difference that this mass is not only shared on single elements but it is distributed on all propositions of the referential of definition $2^\Theta = \{ A/A \subseteq \Theta\} = \{\emptyset, H_1, H_2, ..., H_n, H_1 \cup H_2, ..., \Theta\}$. This referential is built through the frame of discernment $\Theta = \{H_1, H_2, \ldots, H_n\}$, which regroups all admissible hypotheses. These hypotheses must be exclusive. ($H_i \cap H_j = \emptyset$, $\forall$ i $\neq$ j). This distribution is function of the knowledge about the source to model. The whole mass obtained is called « *basic belief assignment* ». The sum of these masses is equal to 1.

4.2 Combination framework

The framework represents all hypotheses which the belief theory is able to manage. It defines our representation of the problem. In our use of the belief theory, each of the framework's hypothesis means that *"the driver is supposed to be in this given state"*, and thus, we need to define our representation of the world through several states that the driver can be in. We use the framework called «*extended open-world*» in order to manage the conflict between sources, and unknown states of the driver [Gruyer 03].

We have not finalized the definition of the frame of discernment. However a simple approach could base the vigilance scale level on driver's tracking performance (*e.g.* lane keeping performance). Such a choice is suitable because "lane keeping" corresponds to a primary driving task and can be easily assessed. As proposed in [Sagberg 04], we split the vigilance decrement process in four stages:

- **State 1 (Y1)**, the driver is awake and his tracking performance is close to optimal
- **State 2 (Y2)**, the driver is in a hypovigilance state and his tracking performance is good, but with lapses.
- **State 3 (Y3)**, the driver is drowsy and his tracking performance is bad and can clearly have risky consequences.
- **State 4 (Y4)**, the driver is about to fall asleep and his tracking performance is catastrophic.

Thus, for a current state of the driver to be recognized as one of the 4 known states Y_1, Y_2, Y_3 and Y_4, we will have the following framework of discernment: $\Theta = \{H_1, H_2, H_3, H_4, H_*\}$ where H_i means that '*the driver is currently in the state* Y_i'. To be sure that the frame of discernment is really exhaustive, a last hypothesis noted 'H_*' is added. H_* means « *the driver state cannot be recognized as a state of our knowledge set* ».

4.3 Expert diagnostic

4.3.1 Problem

A state is seen by a set of sensors (single devices seen in section 2.1), which provide a set of criteria, characterizing this state. Our goal is to compute the confidence in the association between the observed state and a known state (hypothesis of the world). This association is estimated according to several criteria that are obtained from sensors data. This confidence must handle all the available criteria even if they are in conflict. The contrary advice must not reject the relationship between an observed state and the hypothesis (knowledge of the world).

4.3.2 Similarity between an observation and a prediction according to specific criterion

The objective is to define a distance function between two states (an observed and a known state) in order to estimate a level of similarity between them. This similarity is computed for each used criterion (device). This section describes how devices see states, and gives an example of distance function taking into account the data imperfection.

Each expert assesses driver state through specific data coming from the environment. For example, let us consider an expert based on the blinking frequency and duration. The fig 1 shows a qualitative example of how we could represent the different states of the framework for this expert.

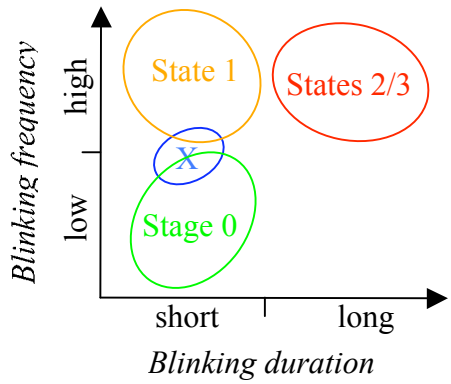


Fig 1: Qualitative framework representation of an expert based on eyes blinking frequency an duration. X represents the current driver's state.

In the literature, we found a great set of distance functions. But in our case, we want a distance of similarity $D_{i,j}$ which answers to the following constraints:

- Firstly, this function $D_{i,j}$ must give a result scaled between 0 and 1 if we are sure that the state i is associated with the other j.
- Secondly, the result must be up to 1 if the state is not associated to the other j.

The distance function also must use both state covariance matrices. The chosen function is an extension of the Mahalanobis' distance [Labayrade 04a].

4.3.3 Generation of the initial mass distributions [Mourllion 05]

The distances of similarities computed from the previous function are used to generate a set of initial mass distributions ($m_j(H_j)m_j(\overline{H}_j)m_j(\Theta_j)$). The mass function generator uses the strong hypothesis: "*the driver can not be and not be in a state in the same time*". In these functions, we can tune a τ parameter in order to be either in a pessimistic or in an optimistic context. In order to generate the masses, we also use both d_j (distance index) and α_0 parameters (reliability on the data source). Then, the initial masses used for the combination and representing the knowledge of the world are the following:

$m_j(H_j)$	Mass associated with the proposition « *the driver is in the state* Y_j. »
$m_j(\overline{H}_j)$	Mass associated with the proposition « *the driver is not in the state* Y_j. »
$m_j(\Theta_j)$	Mass representing ignorance.

4.4 Generalized combination of information

4.4.1 Multi criteria association

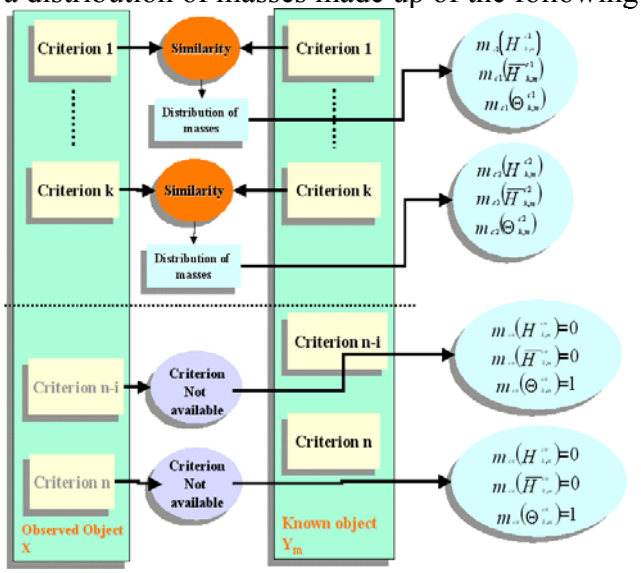
We combine the set of masses distribution built previously in order to obtain a more synthetic set of masses. The set of multi-criteria equations [Gruyer 03] allowing the combinations are computed in a "*closed world*" where the conflict mass is redistributed on the other masses. Nevertheless, we can keep this conflict mass in order to detect a conflict between the criteria.

4.4.2 Full or partial combination

In the case where we have only a sub-part of the full information, we must guarantee a correct processing of the remaining information. This anomaly occurs when we have some asynchronies data and, in this case, only a part of the expert can provide advices. The other one cannot say anything. With our approach, either we do not take into account these experts or we just model the ignorant expert by a full distribution of the mass on $m_{ci}(\Theta_j)$ (see fig 2).

4.4.3 Generalized combination for multi-states association

Now from the set of mass distributions built from the criteria combination, we want to obtain a distribution of masses made up of the following masses:



- $m_{\bullet}(H_j)$: Mass associated with the proposition *"the driver is in the state Y_j."*
- $m_{\bullet}(\overline{H}_j)$: Mass associated with the proposition *"the driver is not in the state Y_j."*
- $m_{\bullet}(\Theta)$: Mass representing ignorance.
- $m_{\bullet}(H_*)$: Mass representing the rejection: "*the driver is not in a known state*".

Fig 2 : Partial or full multi-criteria combination

In this distribution of masses, first index *j* denotes the known states. If this index is replaced by a dot, then the mass is applied to all known states of the frame of discernment.
By observing the behaviour of the iterative combination with *n* mass sets, we detected a general behaviour which enables us to express the final set of masses according to the initial masses distribution. This enables us to compute directly the final masses without any recurrent stage.
Then we deduce from these final masses:

- The singleton hypothesis $m_{\bullet}(H_j)$ and $m_{\bullet}(H_*)$.
- The masses $m_{\bullet\bullet}(H_k \cup \ldots H_l \cup H_*)$ allocated to hypothesis disjunction which are obtained with the use of the equation from [Gruyer 03]. This equation is true for the hypothesis disjunction from the order 2 to the order n-1.
- The regrouping of all disjunctives hypotheses $m_{\bullet}(\Theta)$. It gives a global mass on the "*unknown*".
- The conflict mass $m(\varnothing)$. It is the sum of the multi-criteria combination conflict and the multi-state combination conflict. This mass is useful for quantify either the conflict mass or the assumption "*this state does not exist in the current frame of discernment*". In this second case, it could be a new hypothesis.
- The index *"*"* . It is the notion of *"emptiness"* or more explicitly *"nothing"*. With this hypothesis, we can deduce that a new state has appeared.

In order to establish the best decision on the combination obtained previously, we can use different measures of decision such as credibilistic, plausibilistic, pignistic measurements and then use the max operator. In the following example, we simply use the max level of the singleton final set of masses. This criterion of decision answers the question "*which is the known state Y_j in relation with the perceived state X_i*"?

5. Detailed example

This section shows some results obtained from the combination of expert advices using the belief theory. The aim of this section is to illustrate concretely how belief theory can be applied to vigilance detection. Examples are based on virtual values built in order to confront our approach to classical problems encountered in vigilance detection. These problems are

typically conflicts between sources and false alarm. Following results illustrate the relevance of the use of belief theory in detection of vigilance level.

For both examples, we look at the driving situation through three independent devices (called experts) commonly used in existing research. The three experts are: (*i*) the distance function introduced in section 4.3.2, (*ii*) an expert based on eyelid opening [Dinges 98], and (*iii*) an expert based on SDLP [De Waard 96]. As we said in section 3.1, qualitative reliabilities and accuracy attributes are associated to each expert. Thus, expert 1 gets a reliability level of 0.7 (indirect information on the driver vigilance), expert 2 gets 0.6, (indirect information and sensitive measurement), and expert 3 gets 0.8 (direct information on driver vigilance, but sensitive to driving condition such as weather, traffic volume …).

As frame of discernment, we use the scale proposed in section 4.2, and based on [Sagberg 04]. This scale separate the decreasing vigilance process in four stage: state 1, the driver is awake; state 2, the driver is in hypovigilance; state 3, the driver is drowsy; state 4, the driver is about to fall a sleep.

For each example the normalized distance (section 4.3.2) computed by each expert for each state is given. Distance close to 0 means *"the driver is close to this state"*, distance close to 1 means *"the driver is far from this state"*. As output, combination of expert advice is given. It gives the mass associated to each final hypothesis. A mass close to 1 means *"this hypothesis has a high probability",* a mass close to 0 means *"this hypothesis has a low probability"*. H_i means *"the driver is in the state i"*, $*$ means *"the driver is in an unknown state"*, Θ means *"we don't know in which state the driver is"*, and Ø means *"there is a conflict between expert"*.

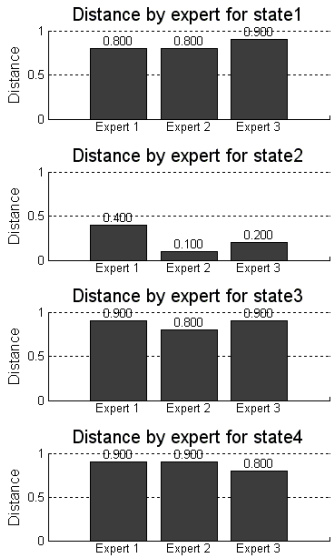


Fig 3: Distances computed by the experts.

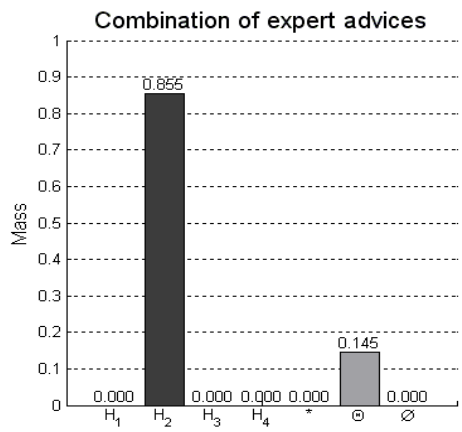


Fig 4: Combination of all expert advice.

In the first example, the driver is in the state 2 (hypothesis 2), which means that's he is in hypovigilance. Fig 3 shows distances computed by each expert for each state. In this example, none of the expert is wrong, so each of them gives the minimum distance for the state 2. Figure 4 gives the final diagnosis, made on the combination of the entire expert diagnosis throw the belief theory. Heaviest mass can be found on the hypothesis 2, meaning that the system recognize that the driver is in the state 2. Although this situation is quite trivial, it shows that our system is able to recognize that there is no conflict between sources. This is shown by the null mass on the hypothesis Θ. This information is important as conflict can easily appears in detection vigilance problems. This will be shown in the two next examples.

In this second example, the driver is awaked (state 1, hypothesis 1). Fig 5 shows distances computed by each expert for each state. We can see that expert 2 gives a wrong diagnosis. A system based on this single device will produce a false alarm. Fig 6 shows the final combination of the entire expert. Consistency of expert 1 and 3 reinforced the right hypothesis H_1 and made a realistic final diagnosis. Belief theory also underlines the occurrence of conflict as shown by a mass Θ hypothesis. This information can be useful in detection of defective device.

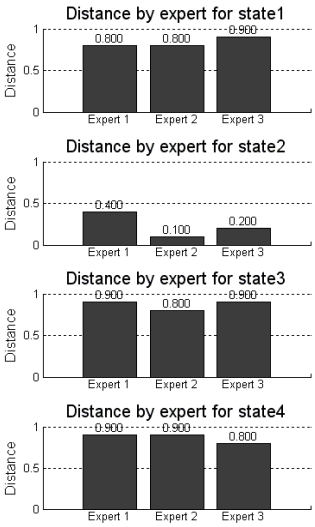


Fig 5: Distances computed by the experts.

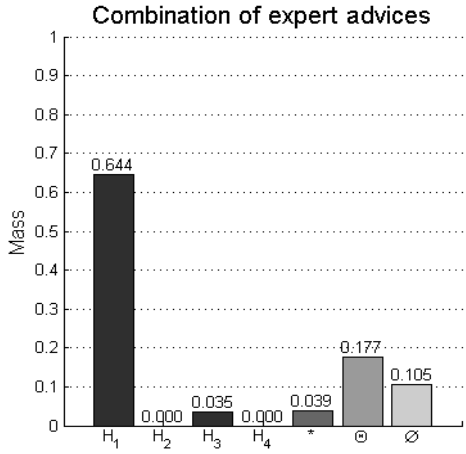


Fig 6: Combination of all expert advice.

In the third example the driver is in state 3. As we can see (fig 7), if we only use expert 1, we can not decide if the driver is in state 2 or 3. Combination of expert 1 and 2 (fig 8) enables us to detect that the driver is in state 3, but a full combination (fig 9) gives a more precise diagnosis. This example shows that the more information that is exploited the more accurate and robust the result is.

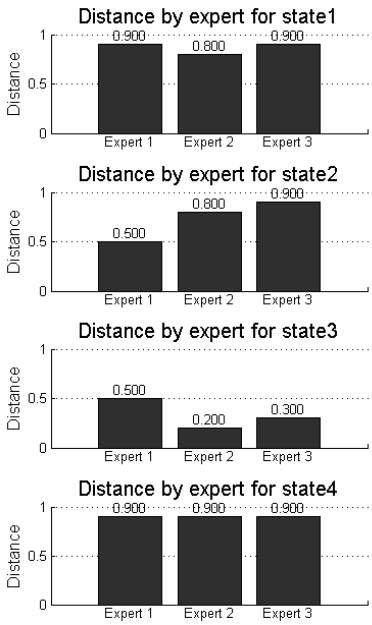


Fig 7: distances computed by the experts.

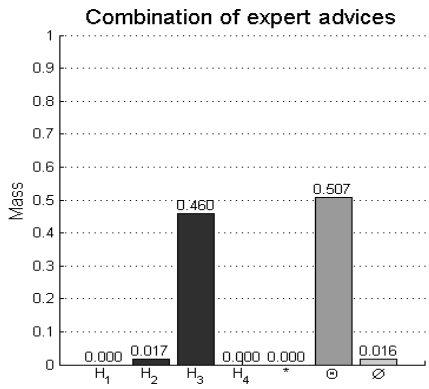


Fig 8: Combination of expert 1 and 2.

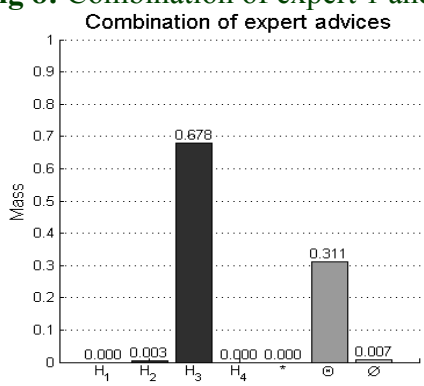


Fig 9: Combination of all expert advice.

6. Conclusion and future works

This paper shows how we use belief theory to assess driver vigilance. Information from the driver, vehicle and environment approach can be merged with this powerful tool, throw existing driving monitoring approaches. Concrete examples show that this new approach is very promising, and that it is able to confront typically problems encountered in detection of vigilance. These examples show that:

- Merging low confidence expert based on Vehicle-Environment-Driver data gives a better final diagnostic (example 3, fig 7, 8 and 9).
- Belief theory is suitable and helpful to manage problems usually encountered in vigilance detection such as false alarm and conflict between expert (example 2, fig 5 and 6).

The examples show results obtain with only three devices (experts), but the final aims is to use the same approach by merging as many devices as available. Notice that in such a fusion system, if a device is momentarily unavailable or if it has been deactivated, then the system still operates properly, thanks to flexibility of the belief theory.

Future works will consist of finalisation, implementation and validation of this theoretical approach. Research plan include the following tasks:

- Definition of the definitive level of vigilance which will be used in the final framework discernment.
- Characterisation of the level of confidence associated to the different devices available in existing works, according to the precedent framework definition.
- Collection of information for the validation stage. For this task we will need to define a significant and accurate scenario, and including validation system such as performance test, intrusive polysomnographie and self evaluation. This will be made according to the survey already made. Driver head pose and eye gaze tracking will be done using FaceLAB system, provided by CARRS-Q. Detection of the environment and vehicle dynamics will be done throw the tools provided by the LIVIC laboratory. Data collection is planned to be made both on simulator and real vehicle.
- Validation of the approach and characterisation of the accuracy of the final system.

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