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A Multi-Facets Analysis of the Driver Status by EEG and Fuzzy Hardware Processing

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Abstract – **In the paper, EEGs are used to perform a multi facets analysis of the driver status. The EEG tracks, taken by means of electrodes installed in a basket dressed by the driver, are processed by a fuzzy model consisting of rules able to predict possible temporary driver attention deficit due to stress or disease conditions. The driving behavior is evaluated in real time by a hardware fuzzy processing. The possibility of taking into account different facets of the driver status is claimed to give rise to a driver control system with good safety and predictive features.**

I . INTRODUCTION

The modern approach to the real time monitoring of the health status makes use of several human bio-signals detected by means of small devices easy to dress. For example, cardio frequency-meters and electronic arterial pressure-meters are more and more used for controlling the shape state of the sportswomen and sportsmen or the status of the old people during their activities. Fusing bio-information coming from different sources increases the precision of the diagnosis.

Therefore, there is a significant interest in developing new micro-instruments able to provide significant information on the health status at condition that they are easy to dress and wirelessly controllable at distance (e.g., by means of Wifi 802.11 or Bluetooth combined with Wimax communication technologies).

Aim of the paper is to discuss how signals taken by Electroencephalograms (EEGs) may be used either alone or in conjunction with other instruments to monitor in real time the drivers status in such a way that incipient conditions that could become in a few time not compatible with the driving activities are timely signaled to a control system which will take suitable actions to avoid road traffic accidents.

As is known, EEGs are widely used to study the electrical activity of the brain and its cortical functional connectivity. In the paper, EEGs are used to perform the attentive analysis of a driver. The EEG tracks are taken by means of electrodes installed in a basket dressed by the driver. The proposed instrument is easier to dress than other sensors proposed in literature to this aim, such as the ones proposed in [1]. A fuzzy model is also illustrated to predict in real time possible temporary driver attention deficit due to stress or disease conditions.

The model consists of a set of fuzzy rules that put into relation the processing in time and frequency of the EEG tracks with the attentive status of the subject under study. The critical conditions are expressed by fuzzy rules that have been identified by a multi facets analysis that takes into account the driver performances, together with the coordination of her/his behavior and her/his drowsiness conditions.

Sect.2 presents a short survey on EEG by pointing out its well known five bands and the related mental states they are able to characterize. In sect.3, the method used to point out the driver status and related relevant variables are presented. Sect.4 proposes a set of EEG based rules that are able, according to the experimental results presented in the paper, to characterize the attention driver deficits due to fatigue or to loss of concentration. The fuzzy version of such rules is presented in sect.5 where the adopted defuzzification formula is discussed. This section briefly illustrates also the architecture of the proposed control system based on four ST-Five fuzzy processors produced by ST Microelectronics.

II . EEG ANALYSIS

EEG measures the voltage difference between the scalp point where an active electrode is placed and the point of the body to which a ground electrode is connected. This voltage difference is generated by the electrical activity of the pyramidal neuronal groups located near to the cortex. EEG signals have an oscillatory nature comprised between 1 and 60 Hz, and an amplitude comprised between 20 and 100 μV.

The EEG tracks are conventionally classified into five types of bands: α, β, γ, δ and θ depending on the frequency and amplitude ranges. Fig.1 shows the typical form of the EEG signals pertaining to the different bands.

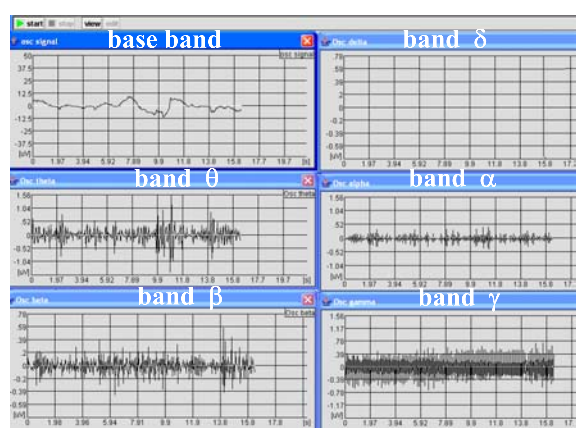


Figure 1: Typical EEG signals

As pointed out in Table I, the EEG bands are related to different mental states [2]. In general, the EEG tracks of high frequency and low amplitude (i.e., β and γ bands) correspond to the mental state of the people engaged (or dreaming to be engaged) in some activity, whereas inactive people (e.g., people sleeping without dreaming or people affected by coma) are characterized by EEG tracks having low frequency and high amplitude (i.e., α, δ and θ bands).

TABLE I
EEG CHANNELS AND MENTAL STATES

Frequency Band	Frequency (Hz)	Amplitude (mV)	Mental States
δ	0,5-3	20-200	Pathologic conditions
ϑ	3 – 7	5 – 100	Sleeping
α	8 – 13	10 – 200	Relaxing
β	14 - 30	1-20	Attention
γ	> 30	1-20	Concentration

From Table I it follows that, in principle, the evolution in time of the α, β and γ bands may be indicative of the driver attention. For example a decrease of the γ band power could be a symptom of fatigue, whereas some incipient sleeping conditions could provoke an increase of the eyes beats frequency that in turn causes an EEG modification.
However, to have a safe evaluation of the driver status it is necessary to be more precise about what types of values deduced from the EEG signals should be taken into account (e.g., mean power, maximum amplitude) and from what zones of the scalp the signals should be measured (e.g., parietal, frontal or central zones). This will be discussed in the next sections.

III . MONITORING METHOD

In the paper one of the following two main conditions are considered enough to say that a people is driving in a not good status, i.e., a) low driving performances due to a low attention or concentration of the driver, and b) physiological problems due to fatigue, fever and so on. We studied a sample of 20 people by a continuous scalp EEG recording. The electrodes were placed according to the extended international 10-20 System shown in fig.2. The scalp potentials were sampled at 250 Hz. The data were filtered between 1 and 50 Hz with a band pass filter (finite impulse response) that leaves the phase of the signal unaltered.
For each person the α, β and γ bands have been recorded for about ten minutes in the following conditions: a) Resting **r(t)**, b) driving with good performances **d(t)**, and c) driving while occasionally reading a newspaper or doing some simple calculations **n(t)**.

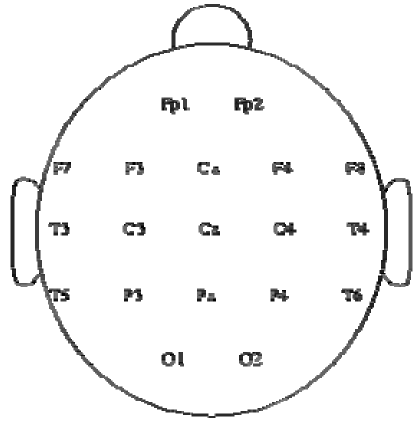


Figure 2: The electrodes are positioned following the 10-20 System

On the basis of these three tracks we have then calculated various types of value (e.g., the mean power of the signal, its maximum amplitude, etc.) in order to verify if they are able to characterize the driver status. Let $Q_j(r)$, $Q_j(d)$, $Q_j(n)$ the values of a certain variable Q_j measured in the three different above mentioned conditions, in the paper such a variable has been considered relevant for our aim if there is a significant difference $D_{d,j}$ between $Q_j(d)$ and $Q_j(r)$ or a significant difference $D_{n,j}$ between $Q_j(n)$ - $Q_j(r)$. Of course, a driver in good shape can be discriminated from a non attentive or seek driver depending on if $D_{d,j}$ and $D_{n,j}$ significantly differ between them.
To make feasible this method, two interrelated problems have to be solved, i.e., a) to identify the most suitable points, called **channels** in the following, of the driver scalp to collect the EEG signals, and b) to establish what **types of processing** of such EEG signals (i.e., what variables Q_j) allows us to characterize the driver status.
In the paper we are not interested in finding a solution that depends on the specific driver such as the one presented in [3]. On the contrary, we aim at solving the mentioned problems a) and b) by rules valid for more or less all the drivers. To find such general rules an experimental approach has been adopted. The experiments that justify why some variables are relevant for modelling the driver status are summarized in the next section. The list of the identified relevant variables is as follows:

Autocorrelation c_{ji} of the EEG signal belonging to the band i taken at the scalp channel j and related **mean power** defined as follows:

$$c_{ji}(k) = \frac{1}{N}\sum_{n=0}^{N-1} x_{ji}(n)x_{ji}(n+k)$$

where x_{ji} is the signal coming from the channel j for the band i, and k is a prefixed lag. As is known, for lag zero, the autocorrelation coincides with the mean power.

Instantaneous frequency f_j and amplitude A_j measuring the difference of the phase ϕ_j of the analytical signal coming from channel j and its amplitude. The instantaneous frequency is defined as follows:

$$f_j(t) = \phi_j(t) - \phi_j(t+1)$$

being ϕ the phase of the analytical signal given by the following expression:

$$\zeta_j(t) = s_j(t) + is_{H_j}(t) = A_j(t)e^{i\phi_j(t)}$$

where i is the symbol of the imaginary part, $s_{Hj}(t)$ is the Hilbert transform of the EEG signal $s_j(t)$ related to channel j, and A_j is its amplitude.

Rhythmicity R measuring the variation of the instantaneous frequency. The lower the R variation, the higher the signal rhythmicity. R is defined as follows:

$$R = \frac{f(t) - f(t+1)}{f(t)}$$

Synchronization S_{ab} measuring how much two channels a and b are in phase between them. S_{ab} is defined as follows:

$$S_{ab} = \left(\left[\frac{1}{N} \sum_{j=0}^{N-1} \sin(\phi_{1,1}(j\Delta t)) \right]^2 + \left[\frac{1}{N} \sum_{j=0}^{N-1} \cos(\phi_{1,1}(j\Delta t)) \right]^2 \right)^{1/2}$$

being $\phi_{1,1}(t) = \phi_a(t) - \phi_b(t)$.

Eyes beats frequency N measuring the number of eyes beats in the time unit and the **eyes closure time T** measuring the time interval during which the eyes are closed in a given beat.

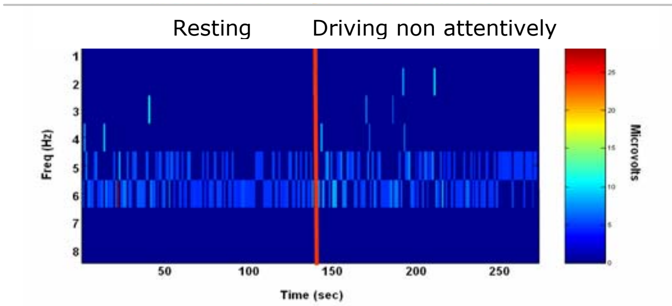
IV . EXPERIMENTAL RESULTS

Concerning the mean power $C_{ji}(0)$, we have found that for 18 people out of the 20 people sample, the most significant channels are: F7F8, F3F4, C3C4, and Pz. Table II shows how much the mean powers of the EEGs of a people driving attentively and non attentively differ from the mean power of the EEG related to her/his resting conditions. Such differences, indicated respectively by Pa-Pr and Pn-Pr, are significant only for the α and γ bands of the signals collected by the electrodes positioned on the mentioned channels.
For the Hilbert analysis the time series were divided into segments of 250 sampling points each corresponding to a window length of 1 sec. The windows did not overlap. For each window the mean instantaneous frequency and amplitude were calculated. To follow the time evolution of the averaged instantaneous frequency and amplitude, a color plot (Hilbert Frequency Amplitude (HFA) plot) was made (Fig.3). This plot shows that when a people passes from a resting condition to a correct driving phase the instantaneous frequency in channel Pz drops from 5-6Hz to 1Hz and the amplitude increase.

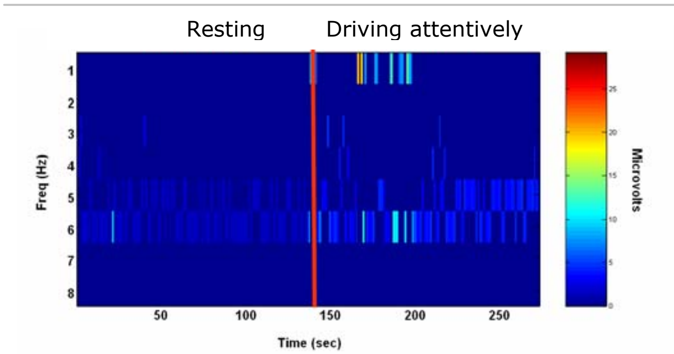
No variation with respect to the resting condition has been observed if the people does not drive attentively.

TABLE II
MEAN POWER RESULTS FOR 18 SUBJECTs ON 20

Channel	Band	Pa-Pr	Pna-Pr
F7F8	γ, α	> 0	<< 0
F3F4	γ	≈ 0	> 0
C3C4	γ, α	< 0	<< 0
Pz	γ, α	>> 0	≈ 0



(a)



(b)

Figure 3: Hilbert Frequency Amplitude (HFA) plot for a people passing from resting to driving non attentively (a) and to driving with attention (b)

Concerning the phase synchronization between different channels, the results drawn in fig.4 show that, for 16 people out of the 20 people sample, during the driving phase the synchronization between the channels Pz-O1O2 and Pz-P3P4 decreases, whereas the one between the channels Pz-F3F4 increases.
Also for the rhythmicity R the time series have been divided into segments of 250 points each with non overlapped windows. R has been computed and averaged for each window. To find characteristic differences between the two phases, we have evaluated the behaviour of this averaged R in the base band. Fig.5 shows that R increases when a people passes from resting to driving non attentively, whereas it decreases for a people passing from resting to driving with attention.

(a)

(b)

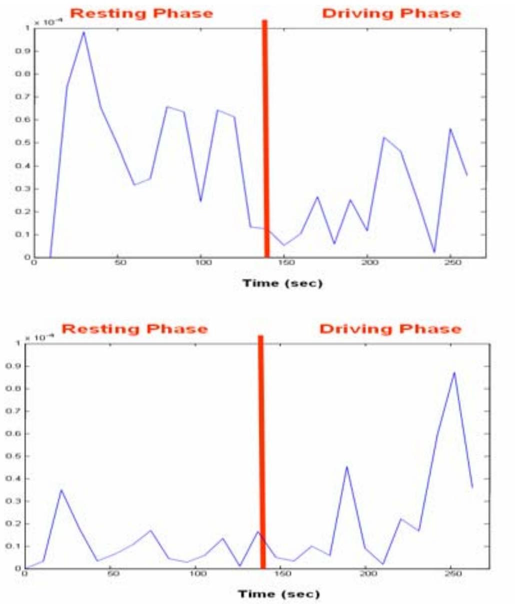


Figure 4: Synchronization between channels Pz-P3P4 (a) and Pz-F3F4 (b) for a people passing from resting to driving attentively.

(a)

(b)

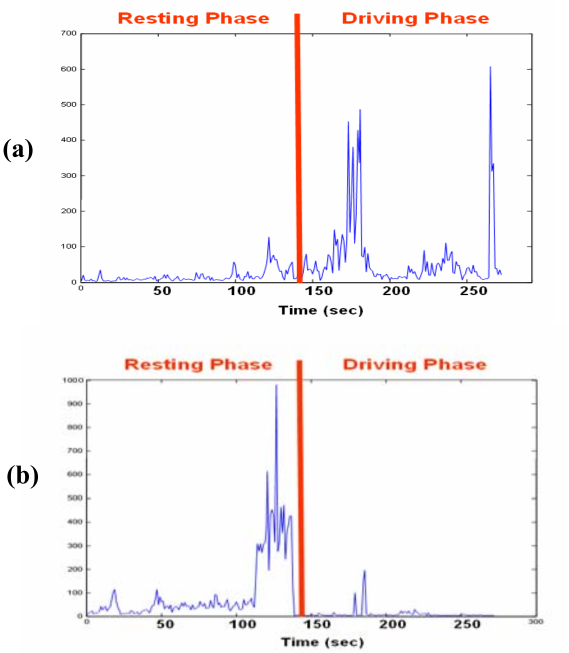


Figure 5: Average Rhythmicity for a people passing from resting to driving non attentively (a) and from resting to driving correctly (b)

Concerning the eyes beat rate and closure time, fig.6 shows that both such values can be detected from the EEG signal collected by applying two electrodes in the positions F_{p1} and F_{p2}. In particular the eye beat is always accompanied by a modification of the base band of the EEG signal characterized by an evident decrease of the signal followed by a significant signal increase. The time interval during which the signal goes down is proportional to the eyes closure time. The number of peaks of the mentioned modifications in the time unit gives the eyes beat rate.

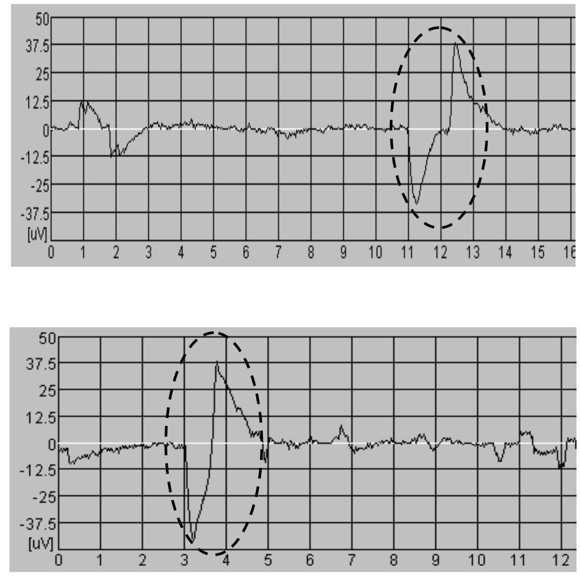


Figure 6: Modifications of the base band of the EEG signal corresponding to two different eyes beats: the related signal modifications have always the same waveform.

V. FUZZY SYSTEM

On the basis of the experimental results previously presented, in this section we illustrate the system we have implemented for monitoring the driver status. It consists of four fuzzy subsystems.

The **first subsystem** aims at evaluating the performances of the driving activity by taking into account the EEG mean power differences shown in Table I. This agrees with other studies that characterize the driving performances by EEG power measurements, e.g., the power spectrum and the principal component analysis [3]. The **second subsystem** is conceived to analyze a sort of driving coordination since it takes into account the frequency and amplitude variations in time (fig.3), rhythmicity (fig.4), and the interchannel synchronization (fig.5). This agrees with other studies on the coordination of the human brain such as [4], [5], [6]. The **third subsystem** is designed to evaluate the physiological status and related drowsiness (fig.6).

To take into account all the mentioned information contemporaneously, the output of each subsystem will be passed to a **fourth subsystem** to obtain a multi facets evaluation of the driver status.

Fig.7 shows the general architecture of the proposed system. The inputs of the first subsystem are the variations of the mean powers for the channel F7F8 (bands γ, α), F3F4 (band γ), C3C4 (bands γ, α) and Pz (band γ). Such differences are suitably normalized between 0-255 so that it is possible to compute the evidence of the fuzzy expressions $<< 0$, < 0, ≈ 0, > 0, $>> 0$ by using the membership functions shown in fig.8. By such evidences, the first fuzzy subsystem is able to compute the fuzzy rules concerning the performances of the driving activity in terms of EEG mean power accordingly to our experiments.

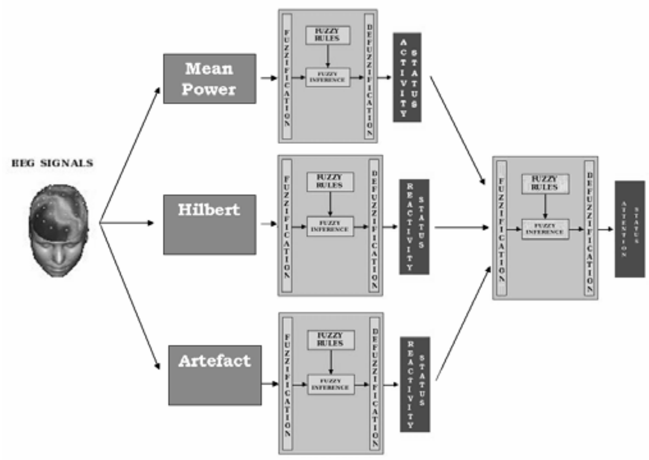


Figure 7: Proposed system for attention analysis

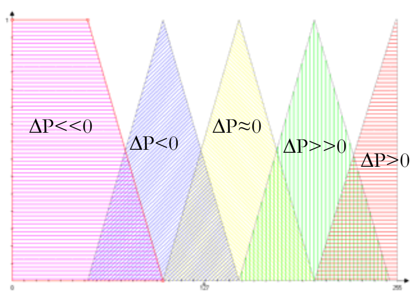


Figure 8: Membership functions to evaluate the evidences of the fuzzy expressions $\Delta P \ll 0$, $\Delta P<0$, $\Delta P \approx 0$, $\Delta P>0$, $\Delta P \gg 0$

Some fuzzy rules followed by the first subsystem are as follows:

if $\Delta P_{\gamma F7F8}$ *is << 0 and* $\Delta P_{\gamma F3F4}$ *is > 0* $\Delta P_{\gamma C3C4}$ *is <<0 and if* $\Delta P_{\gamma Pz} \approx 0$ *is the Output is Low;*

if $\Delta P_{\alpha F7F8}$ *is << 0 and* $\Delta P_{\gamma F3F4}$ *is > 0 and* $\Delta P_{\alpha C3C4}$ *is << 0 and if* $\Delta P_{\alpha Pz} \approx 0$ *the Output is Low;*

if $\Delta P_{\alpha F7F8}$ *is < 0 and* $\Delta P_{\gamma F3F4}$ *is >> 0 and* $\Delta P_{\alpha C3C4}$ *is << 0 and if* $\Delta P_{\alpha Pz} \approx 0$ *the Output is Middle-Low;*

if $\Delta P_{\alpha F7F8}$ *is > 0 and* $\Delta P_{\gamma F3F4}$ *is* ≈ 0 *and* $\Delta P_{\alpha C3C4}$ *is* ≈ 0 *and if* $\Delta P_{\alpha Pz}$ *>> 0 the Output is High;*

In these rules, the consequents may have the value *High, Middle High, Normal, Middle Low,* or *Low* depending on the driving performances. In our implementation, the membership functions of the rule consequents are singletons, since they are defined for only one point as shown in fig.9. The output of the first fuzzy subsystem is a crisp number obtained by defuzzifying the rules according to the following formula:

$$out(crisp) = \frac{\sum_{i=1}^{N} (rule\_evidence * \sin gleton)_i}{\sum_{i=1}^{N} (rule\_evidence)_i}$$

where rule_evidence (i.e., the evidence of the consequent of the rule) is the minimum of the evidences of the fuzzy expressions contained in the antecedent of the rule. The output will be given by a number comprised between 50 (corresponding to low driving performances) and 250 (corresponding to high driving performances).

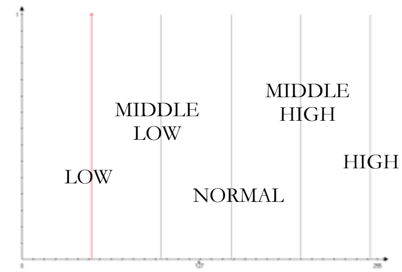


Figure 9: Membership functions of the output

The inputs of the second fuzzy subsystem related to the coordination of the driver behavior are: the variation of the mean rhythmicity (*ΔR*), the instantaneous frequency (*f*) and the variation of the instantaneous amplitude (*ΔA*) in channel Pz, the variation of the phase synchronization of the channels F3F4, F7F8, O1O2 and P3P4 with Pz (*ΔFi*).

Some fuzzy rules followed by the second subsystem are as follows:

if ΔR is <0 and f is high and $\Delta F_{Pz-0102}$ *is <0 and if* $\Delta F_{Pz-P3P4}$ *is <0 and* $\Delta F_{Pz-F3F4}$ *is <0 and if* $\Delta A \approx 0$ *then Output is Low;*

if ΔR is <0 and f is high and $\Delta F_{Pz-0102}$ *is* ≈ 0 *and if* $\Delta F_{Pz-P3P4}$ *is <0 and* $\Delta F_{Pz-F3F4}$ *is <0 and if* $\Delta A \approx 0$ *then Output is Middle-Low;*

if ΔR is <0 and f is middle and $\Delta F_{Pz-0102}$ *is < 0 and if* $\Delta F_{Pz-P3P4}$ *is* ≈ 0 *and* $\Delta F_{Pz-F3F4}$ *is* ≈ 0 *and if* $\Delta A \approx 0$ *then Output is Normal;*

if ΔR is >0 and f is low and $\Delta F_{Pz-0102}$ *is* ≈ 0 *and if* $\Delta F_{Pz-P3P4}$ *is* ≈ 0 *and* $\Delta F_{Pz-F3F4}$ *is <0 and if* $\Delta A > 0$ *then Output is High;*

In the above rules, the evidences of the fuzzy expressions *<0, ≈ 0,* and *>0* are given by the membership functions shown in fig.10.

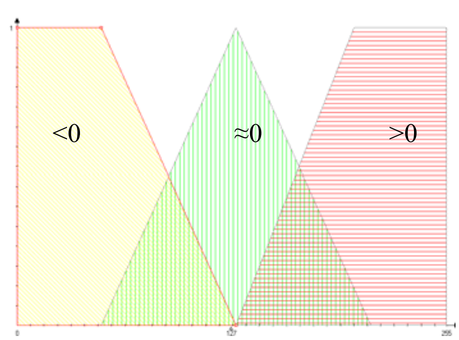


Figure 10: Membership functions to evaluate the evidences of the fuzzy expressions <0, ≈0, >0

The membership functions corresponding to *Low, Middle,* and *High* of the antecedents have the typical trapezoidal form, whereas the consequents of these rules are singletons and may have the value *High, Middle High, Normal, Middle Low,* or *Low* depending on the driving coordination. The output of the subsystem is a crisp number obtained according to the mentioned defuzzification formula.

Concerning the fuzzy subsystem devoted to evaluate the drowsiness, it consists of two inputs: the number of beats (N) and the closure time (T) of the eyes. Fig.11 shows the membership for the eyes closure time.

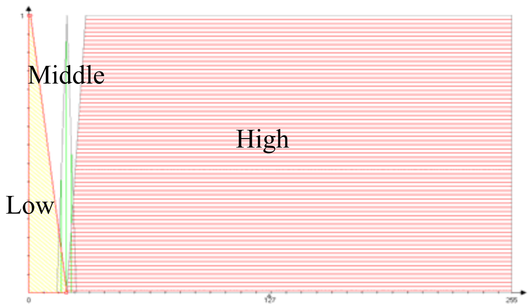


Figure 11: Membership functions for the eyes closure time

Some fuzzy rules followed by the third subsystem are as follows:

if T is high and N is high then Out is High
if N is middle and T is low and then Out is Low
if T is middle and N is middle then Out is Normal
if N is middle and T is low and then Out is Low

Also in these rules, the membership functions corresponding to *Low, Middle,* and *High* of the antecedents have the typical trapezoidal form. The consequents are singletons and may have the value *High, Normal,* or *Low* depending on the driving drowsiness. The subsystem output is a crisp number obtained according to the mentioned defuzzification formula.

All the outputs of the three previous subsystems are passed to the final fuzzy subsystem to calculate the status of the driver. Some fuzzy rules followed by the final subsystem are as follows:

if activity_status is high and coordination_status is high and drowsiness is low Out is High;

if activity_status is low and coordination_status is high and drowsiness is low Out is Middle-Low;

if activity_status is low and coordination_status is low and drowsiness is high Out is Low;

if activity_status is high and coordination_status is low and drowsiness is low Out is Low.

Also in this case, the membership functions of the antecedents have the typical trapezoidal form, whereas the consequents are singletons and may have the value *High, Normal,* or *Low.* The output of the final subsystem is a crisp number, obtained by the above defuzzification formula, that characterizes the overall driving status.

VI . CONCLUDING REMARKS

An EEG based model of the driver behaviour has been presented. Such model consists of three set of rules pertaining to different facets of the driver status, i.e., driving performance, coordination of the behaviour while driving, and drowsiness. Considering contemporaneously all the facets increases the system safety. In fact, in the experiments, we have found that for any people of our sample the critical driving status is always revealed by the firing of at least one set of the proposed rules. Moreover, if all the three sets of rules are able to monitor a facet of the driver status, considering all the facets contemporaneously makes it possible to predict the emergence of a critical driving status. A deep discussion on this subject is for further study.

Each fuzzy system has been implemented by using the chip St52f513 produced by ST Microelectronics that allowed us the implementation of the Mamdami type fuzzy inferences with crisp consequents adopted in the paper. The developed prototype is shown in fig.12. An enhancement of the prototype is planned in order to allow us to wirelessly collect the EEG tracks of the driver and to obtain a more clear characterization of the driver status by possibly using more channels than the ones considered in the paper.

Figure 12: EEG based prototype for monitoring the driver status based on four STFive fuzzy processors

VII . REFERENCES

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