Analysis of Drivers' Responses under Hazardous Situations in Vehicle Traffic

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***Abstract*— This study focused on the analysis of drivers' reactions under hazardous scenarios in vehicle traffic. Driving behavior signals were utilized to detect a chain of changes in driver status and to retrieve incidents from a large real-world driving database obtained from the Center for Integrated Acoustic Information Research (CIAIR). All the existing 25 potentially hazardous scenes in the database were hand-labeled and categorized. A new feature, based on joint-histograms of these behavioral signals and their dynamics was proposed and utilized to indicate anomalies in driving behavior. Brake pedal force-based method attained a true positive (TP) rate of 100% for a false positive (FP) rate of 4.5%, concerning the detection of 17 scenes where drivers slammed on the brakes. Results stressed the relevance of individuality in drivers' reactions for this retrieval. In 11 of the 25 hand-labeled scenes, drivers reacted verbally. Scenes where high-energy words were present were adequately retrieved by the speech-based detection, which achieved a TP rate of 54% (6 scenes), for a FP rate of 6.4%. In addition, the proposed integration method, which combined brake force and speech signals, was satisfactory in boosting the detection of the most subjectively dangerous situations.**

I. Introduction

A. Problem Statement

On the last decade, experts from academia and industry have been actively involved in road safety. Efforts devoted to promote safer, more comfortable, and more efficient transport are mainly concentrated in two areas: accident prevention and injury reduction. The former has been effective in promoting infrastructure improvements and in raising driver awareness, addressing inappropriate or hazardous behaviors [1][2], while the later has primarily focused on the advancement of vehicular safety systems [3][4]. The above efforts have positive impacts and implications in human, urban, and scientific levels, respectively: (a) reduction of traffic deaths and injuries; (b) better traffic organization and reduction of costs; (c) better understanding of human behavior during a dangerous situation.

Although encouraging improvements in transportation have been made, the number of road fatalities and injuries is still unacceptably high, suggesting that these measures alone do not suffice. In 2005, road accidents killed over 7,500 people in Japan, and injured more than 900,000—a high price has been paid for urban mobility.

Statistics have shown that almost 95% of the accidents are partially due to human factor [2]. In almost three-quarters of the cases the human behavior is solely to blame. Recently, heavy investments have contributed in releasing cutting-edge systems, technologies and applications; however, figures indicate that far more effort has to be put into a better understanding of drivers' reactions during hazardous situations.

Each individual driver is likely to perceive traffic conditions differently and take risks according to his/her own judgment. Besides, the intensity of reactions may vary due to multiple factors such as gender, age, and driving experience. It is reasonable to expect that, during a hazardous situation, drivers' responses change accordingly. Nevertheless, only a very small number of systems have laid particular stress on the need for models which take into account drivers' individuality [5].

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In addition, models should take into account the complexity of hazardous situations and recognize the multi-modal nature of drivers' behaviors to be more closely related to real conditions. Although most of the systems relate traffic incidents to a small set of maneuvers, a dangerous situation is often due to multiple factors, including human behavior. In this context, there is a necessity to identify the chain of changes in human conduct to better characterize a hazardous situation.

Correspondingly, to gain insight into drivers' reactions to dangerous circumstances, this study intended to explore the relevance of driving behavior individuality concerning the detection of hazardous situations and the integration of multi-modal reactions to hazard in order to improve detection robustness.

B. Research Approach

In order to achieve research goals, a method for mining potentially hazardous situations in a multimedia driving database was proposed and evaluated based on the reactions of drivers to danger. Besides a better understanding of drivers' responses to hazard, mining results can be utilized to proactively promote safety—differently from reactive methods, such as pre-crash sensing [3], that aim at predicting eminent risks for drivers.

An application which acts proactively and has increasingly attracted attention is the drive recorder [1][6]. Triggered by sudden accelerations or decelerations, the system stores vehicle and surroundings information immediately before an accident or a near miss incident. Mostly utilized by taxi drivers (notably in Japan), recorded data helps, for example, in the detection of drivers who need instructions and advice on road safety manners and attitudes. In addition, mining results can be also utilized to create a database of real-world potentially hazardous situations. Currently, a large number of experiments in this research area are performed with the aid of simulations.

The proposed detection method utilized multimedia driving behavior signals, namely force on the brake pedal or speech or both, to perform a mining task. A new representation of these signals was first proposed to elucidate anomalies, which represented responses to potentially hazardous circumstances. A following hand-labeling and categorization of potentially hazardous scenes presented in the database were done, and labels utilized to evaluate the detection. Results were analyzed and conclusions about drivers' reactions under hazardous situations were drawn.

The relevance of behavior individuality was addressed by settling a detection approach that took into account individual characteristics of drivers and contrasting it with an ordinary approach. In addition, a method for the integration of two multimedia features in order to boost detection was proposed and analyzed. This method was based on the combination of reactions detected through brake pedal and speech.

In the following sections, a brief introduction of the database and its preparation is given, followed by an explanation of the proposed feature for detection. We then offer descriptions of the detection methods and results. Finally, discussion and future work are presented.

II. Database and Preparation

The driving data utilized in this work was obtained from the Center for Integrated Acoustic Information Research (CIAIR) [7], Nagoya University. Multimodal information was collected in a vehicle under both driving and idling conditions. The database is composed of images, control (driving), and location signals that were recorded synchronously with speech. Drivers were asked to interact with both, a human operator (HUM) and a Wizard of Oz system (WOZ) [8], and perform simple speech tasks such as asking information about the weather or restaurant locations.

For this study, HUM session data from 373 drivers (34h), recorded from November, 2000 to March, 2002 was utilized. HUM session was chosen mainly because its data is more closely related to everyday conditions; however, WOZ session data was utilized as a training set, further explained in session III.

A. Hand-Labeling

Situations were selected by taggers from 34 hours of video footage. A potentially dangerous situation to be included in the test was defined as any motion by some other road user, which could possibly develop into a hazard, and for which the driver had to be especially prepared for taking some evasive action in terms of braking or steering. In-car videos were taken from two different viewpoints: drivers' face and frontal view. In addition, in order to avoid missing any potentially hazardous scene in the database, drivers' reactions, scrutinized utilizing the brake pedal force, steering wheel angle, and speech were also taken into account when labeling. Specifically, taggers focused on the following behaviors, since it was more likely that something hazardous had occurred when they were observed:

- Sudden and strong use of the brake pedal;
- Sharply turning the steering wheel;
- Expletive words;
- Anxious facial expressions.

Data was divided into five groups, and five taggers performed the labeling task. Results were then shown to two more taggers in order to validate the potentially hazardous situation. Taggers were voluntary graduate students, with no technical skills of traffic incidents or accidents, so the final number of selected potentially dangerous scenes may have been affected.

The 25 dangerous scenes that already existed in the database were labeled considering that the start point was the initial change in driver behavior, detected subjectively by analyzing the pedal and steering signals, and watching in-car videos. The end point was set when the "normal" condition, observed before the start point, returned. A margin of one second before the start point and after the end point of each hand-labeled potentially hazardous situation was included.

Although in all the 25 hand-labeled scenes drivers were aware of the circumstance, which could possibly develop into a hazard, risks were considered acceptable in five of them and no substantial reactions were observed. Besides, drivers uttered expletive words to express negative feelings in eleven of the 25 situations selected as potentially hazardous. In 17 of these 25 situations, sudden and intense compression of the brake pedal was observed. In eight situations, both reactions were present. In three, only the use of expletive words was verified.

B. Ranking According to the Level of Dangerousness

In order to objectively verify the relationship between the level of driver's reactions—detected through brake pedal force as well as speech—and hazard, a raking based on the subjective level of dangerousness was proposed.

The definition of each level was shown to six taggers, who watched once the 25 potentially hazardous scenes of the HUM data. Scenes were than shown again, and taggers were asked to assess risk levels based on video footage and audio only. No driving signals were shown in order to avoid biased results. It was stressed to taggers not to take into account drivers' reactions, only the environment. So, if a driver's reactions to a certain potentially dangerous situation were particularly strong, but the scene was subjectively of low hazard, the "Low" label was given to it. Potentially dangerous situations were ranked according to the following definition. Concerning the potentially hazardous situation:

A) Low - No additional maneuvers are required unless they can be implemented at very low cost (in terms of time and effort). Actions to further risk reduction are assigned low priority;

B) Medium - Consideration should be as to whether the risks can be lowered, where applicable, to a tolerable level and preferably to an acceptable level, but the costs of additional risk reduction measures should be taken into account. The risk reduction measures should be implemented within a defined time period. Arrangements should be made to ensure that vehicle controls are maintained;

C) High - Substantial efforts should be made to reduce the risk. Risk reduction measures should be implemented urgently within a defined period of time. Considerable resources might have to be allocated to additional vehicle control measures.

A value was assigned to each scene, depending on its level—1 for low, 2 for medium and 3 for high—and the mean score of each scene was calculated. Using the mean score as the input vector, scenes were divided into three groups using the K-means algorithm [9].

Ranking results are as follows: Group A (low) with 9 scenes, Group B (medium) with 14 scenes and Group C (high) with 2 scenes. Three of the five situations, explained in section II-A, in which no substantial reactions from drivers was observed, were ranked as having a low level of dangerousness. The other two, as having a medium level. Since taggers were voluntary graduate students, with no technical skills of traffic incidents or accidents, the final content of each group may have been affected.

III. Brake Pedal Force-Based Detection

This section describes the detection of situations when drivers slammed on the brakes. Since this is a maneuver characterized by a strong and sudden use of the brake pedal, a feature which took into account not only intensity, but also the dynamics of the compression was necessary. In this study, an alternative representation of the brake pedal signal was proposed.

Figure 1 shows a 6-second interval when the driver strongly compressed the brake pedal. The solid and dashed lines indicate brake pedal force and its dynamics, respectively. One of the most common forms of the dynamical behavior of a signal is the estimation of linear regression coefficients, which are calculated in the following way for a signal $x(n)$ with a window of length $2K$:

$$\Delta x(n) = \frac{\sum_{k=-K}^{K} k x(n+k)}{\sum_{k=-K}^{K} k^2}. \qquad (1)$$

The relationship between the two signals illustrated in Fig. 1 can be fully appreciated by plotting them on a single graph, with the

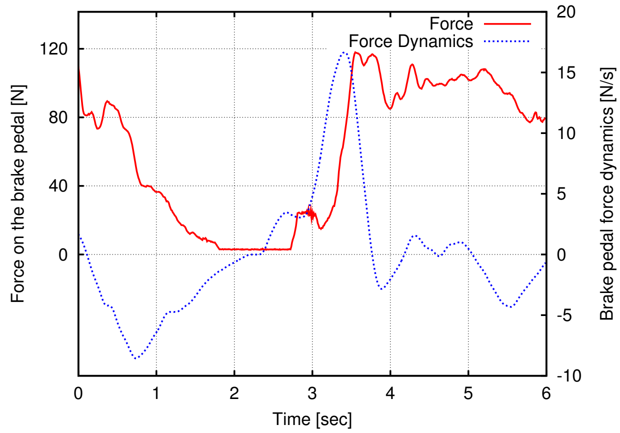

Fig. 1. 6-second interval of brake pedal force signal (solid line) and its dynamics (dashed line).

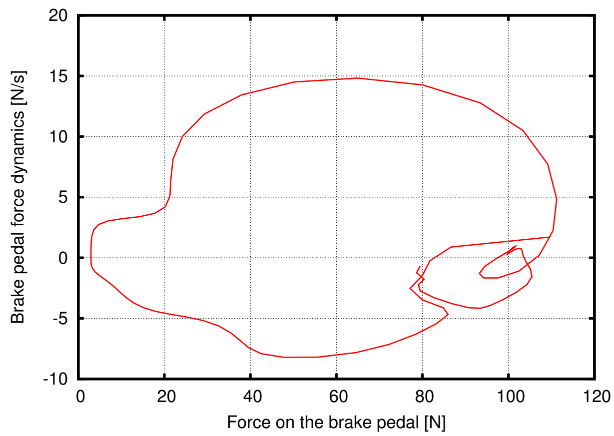

Fig. 2. Joint plot of brake pedal force and its dynamics.

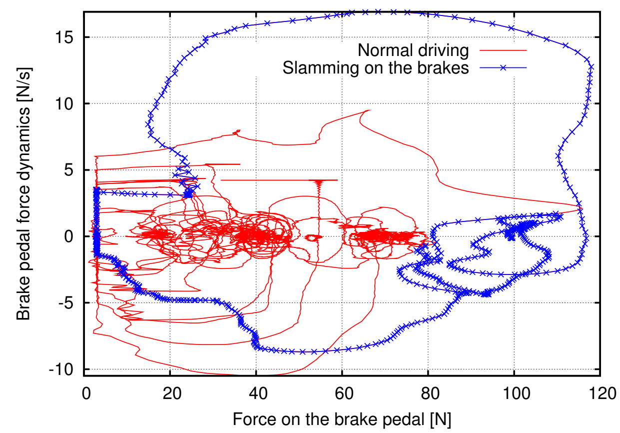

Fig. 3. Joint plot of a 5-minute interval of brake pedal force and its dynamics. The line with crosses represents a sudden and strong braking.

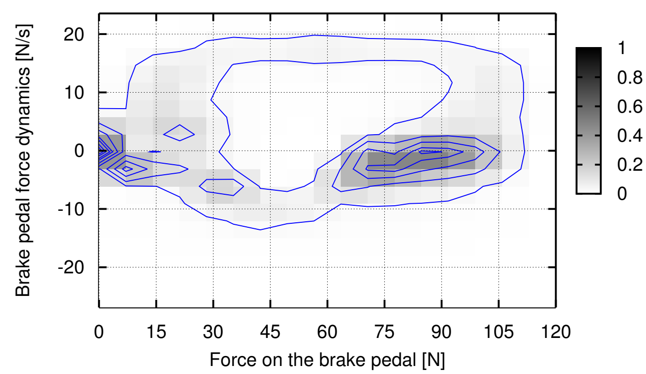

Fig. 4. Joint-histogram of brake pedal force and its dynamics.

x-axis denoting the force and the y-axis denoting the dynamics. Figure 2 shows the joint plot, smoothed with Bezier smoothing. Each point in this graph represents a temporal state of the system, which changes as we travel clockwise around the curve. The start of the cyclic process is a point close to 0N/s and 110N—an idling condition. The driver then released the brake pedal and the left-most point, around 0N/s and 0N, was reached—a forward motion started. A following strong braking took again the vehicle to an idling condition, a point around 0N/s and 80N. The cyclic nature of the process elucidates its dynamical behavior.

An analysis of the same type of joint plot in the long run, shown in Fig. 3 for a 5-minute interval, reveals areas where data concentrates. One large area, with force dynamics around 0N/s and force ranging from, approximately, 10N to 80N represents an idling status. A region around 0N/s and 0N represents a normal moving condition. These are ordinary driving circumstance at most of the five minutes. An inspection in Fig. 3 indicates that there is also an anomaly in the system. The blue line with the cross symbols over it represents the 6-second interval of Fig. 2, when the driver slammed on the brakes. To detect such data which deviates from the ordinary driving conditions a clustering analysis was adopted, since it has been utilized satisfactorily to solve anomaly detection problems. In this study, the Linde-Buzo-Gray (LBG) algorithm [10] was chosen as the clustering scheme, since it is less sensitive to initial parameters than well-known algorithms such as K-means [9].

A joint-histogram of brake pedal force and its dynamics was utilized to describe the cyclic data, such that in Fig. 2. A joint-histogram of data presented in Fig 2 is shown in Fig. 4. Ordinary driving conditions, represented by the concentration of cycles as those in Fig. 3, were characterized by a clustering of histograms generated from consecutive data frames. The detection was then performed by calculating the distortion from each frame histogram to clusters, which represented a *safety model*. The distortion of a given histogram was obtained by calculating its Euclidean distance from clusters and taking the minimum of them. Data frames which the distortion overcame a certain threshold barrier were labeled as potentially hazardous.

The Euclidean distance of two 2D histograms h_1 and h_2 of L^2 bins was calculated as follows:

$$dist = \frac{1}{L^2}\sum_{i=l}^{L}\sum_{j=l}^{L}(h_1(i,j) - h_2(i,j))^2. \quad (2)$$

The sparsity of potentially dangerous scenes in the database was a significant limitation, and made it intractable to also devise a dangerousness model. Accordingly, the safety model approach was adopted. Moreover, to avoid detecting strong compressions of the brake pedal which occurred during an idling condition, vehicle velocity was also considered as a detector input. Frame intervals which mean velocity did not overcome a certain threshold barrier were labeled as not dangerous.

A. Training and Test Sets

This section describes different types of training and test data sets which were utilized during the experiments. A training set indicates data utilized as the clustering analysis input. On the other hand, a test set corresponds to data compared to clusters in order to have its distortion from the safety model calculated. As mentioned in section II, drivers interacted with two different dialog partners—HUM and WOZ. Consequently, the following sets could be proposed:

1) Set 1: For each driver, data from the HUM session was utilized in training and test sets;
2) Set 2: For each driver, data from the WOZ session was utilized in training set and data from the HUM session in the test set;
3) Set 3: HUM session data of all drivers was utilized to create a single model of safety. Test data for each driver was taken from the HUM session;
4) Set 4: WOZ session data of all drivers was utilized to create a single model of safety. Test data for each driver was taken from the HUM session.

In sets one and two, a *driver-dependent clusters approach* was utilized, since a different safety model was generated for each driver. Nevertheless, in sets three and four, a *driver-independent clusters approach* was adopted, given that the safety model was the same for all drivers. Since potentially dangerous situations were very sparse in the database, their data was also included in the training set.

Different types of detection thresholds were also considered when performing the detection. The threshold could be set to:

1) Driver-independent: the same for all drivers;
2) Driver-dependent: an individual threshold.

A threshold adjusted for each driver was important since the intensity of reactions varies, for example, according to gender. Mean (μ) and standard deviation (σ) of frame distortions were calculated and the threshold was set to $\mu + \alpha\sigma$, where α was the same for all drivers.

B. Uniqueness of Driver Behavior

Drivers express their individuality both consciously and unconsciously when driving. While searching for pertinent individual characteristics, recent efforts toward biometric signature using driving behavior [11][12], have stressed the relevance of certain features, such as the way gas and brake pedals are compressed.

To verify the role drivers' individuality regarding the detection of hazardous situations, a comparison of two detection approaches was proposed. One took into account individual characteristics of each driver, while the other did not. In both of them, driver-independent clusters were created and utilized as the safety model. Along with a driver-independent threshold approach, a detection that does not rely on individualities could be devised: model and parameters were the same for all subjects. Nevertheless, a driver-independent cluster approach together with a driver-dependent threshold calculation took into account the individuality of each driver, allowing an interesting comparison with the first approach.

C. Enhancement of Low Amplitude Areas

Dark areas in Fig 4, where cycles concentrate, indicate values of brake pedal force and its dynamics that were presented most of the time. Light areas indicate the movement from idling to moving condition, and then back again to the idling condition after a strong use of the pedal (the process moves clockwise). These light areas play a fundamental role, since they tell us how the change between conditions occurred. To better represent the light areas as a feature, an enhancement step before the LBG clustering stage was proposed. A normalization process, which made the maximum value in the histogram equal to one and the following mapping comprised this step:

$$y = x^{\gamma}. \tag{3}$$

Where x is the original histogram value and y is the mapped one, utilized as an element of the clustering algorithm input vector. γ is the degree of enhancement. Values close to one (maximum) do not considerably change after the mapping, while low amplitude regions can be greatly enhanced, depending on γ.

D. Detection Evaluation

When the distortion from clusters of a certain frame overcame the threshold barrier, the next eight seconds were considered one potentially dangerous scene; therefore even if multiple hits inside this interval were observed, only one valid detection was counted. An 8-second interval, chosen based on the hand-label results, was set as the duration of a dangerous situation. When detection was observed inside the hand-labeled limits of a hazardous scene, a true positive detection was counted. Results are presented utilizing Receiver Operating Characteristics (ROC) graphs [13]. The following definitions were also utilized for displaying ROC graphs:

- Total positives: the number of hand-labeled potentially dangerous scenes in the test data. However, when detecting, for example, the 17 scenes of HUM data where a sudden and strong use of the brake pedal was observed, the number of total positives was set to 17;
- Total negatives: the number of 8-second frames inside the test data minus the number of 8-second frames inside the hand-labeled dangerous situations.

Experiments for this detection method were performed for different values of enhancement γ (0.05, 0.1, and 0.2), histogram bins (144, 256, and 576), clusters (2, 4, and 8), frame length (2s, 4s, and 8s), frame shift (1s, 2s, 4s, and 8s) and velocity threshold (0-8km/h). A delta feature window of 800ms was utilized in all experiments. Optimal parameters, which achieved less false positive detections, were obtained by changing one parameter at a time, while keeping other fixed.

E. Brake Pedal Force-Based Detection Results

The best result for brake pedal force-based detection was achieved with 256 bins, 2 clusters, frame length and shift of 4.0s and enhancement $\gamma = 0.05$. The optimal velocity threshold was 4km/h. Above this value, 100% of detection was not achieved. A driver-independent clusters approach trained with HUM data, along with a driver-dependent threshold, attained the best performance. Similar results were obtained for a driver-independent approach trained with WOZ data and a driver-dependent threshold.

Since the focus of this section is on mining sudden and strong compressions of the brake pedal, results are relative to the detection of the 17 scenes where a strong use of the brake pedal was observed. Fig. 5 shows the detection results as ROC graphs, obtained by varying the detection threshold, as explained in section III-A. Best

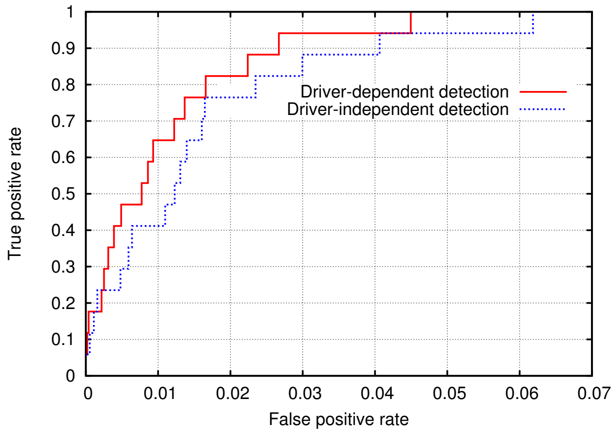

Fig. 5. Best results for brake pedal force-based detection utilizing driver-dependent and driver-independent approaches.

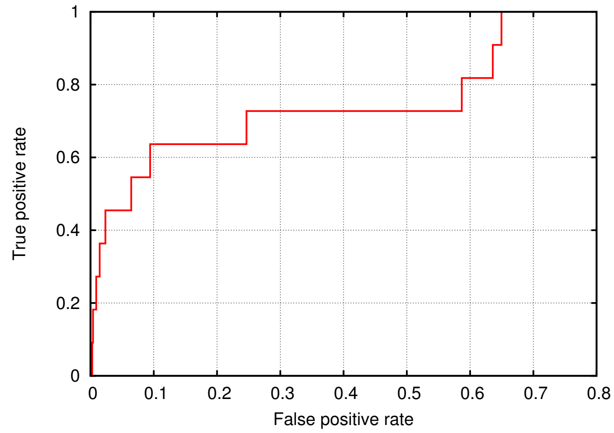

Fig. 6. Best results for speech-based detection.

results for both driver-dependent and driver-independent detections, as explained in section III-B, are shown.

IV. Speech-Based Detection

The possibilities for a multi-modal analysis of drivers' reactions during hazardous circumstances are varied. Slamming on the brakes and sharply turning the steering wheel are, for example, intuitive responses in a dangerous traffic situation. Under certain conditions, however, suddenly pressing the brake pedal or a rapid steering wheel movement are unsafe practices. Therefore, in this scenario, natural reactions such as uttering some words or non-verbal sounds to express negative feelings about an adverse condition are relevant facets to be analyzed.

An analysis of the hand-labeled potentially dangerous situations stressed the advantages of using speech as a feature in this research. Scenes where a sharp turning of the steering wheel was observed, a sudden and strong use of the brake pedal was also present. The same was not true for verbal responses, as mentioned in section II-A.

This method followed an analogous approach as that explained in section III. Sudden and high energy speech utterances presented similar anomalous characteristics as sudden and strong braking; therefore the joint-histogram of speech energy and its dynamics was utilized as feature. The detection evaluation followed the method described in section III-D.

Experiments were performed for different values of enhancement γ (0.1, 0.5, and 1.0), histogram bins (49, 64, and 144), clusters (2, 4, 8, and 16), frame length (1s and 2s), and frame shift (0.5s and 1.0s) for global and individual clusters approaches. A delta feature window of 960ms and a driver-dependent threshold were utilized in all experiments.

A. Speech-based Detection Results

The best result for speech-based detection was achieved with 64 bins, 4 clusters, frame length of 1.0s, shift of 0.5s and enhancement $\gamma = 0.5$. The detector trained with a driver-dependent clusters approach of HUM data presented the best performance.

Since the focus of this section is on mining expletive words, results are relative to the detection of the 11 scenes where drivers reacted verbally to the hazardous situation. Results are shown in Fig. 6 as ROC graphs, obtained by varying the detection threshold.

V. Integrating Information Sources

This section describes the integration of two different sources of information—brake pedal force and speech—for the detection of potentially hazardous situations. One possible strategy is to combine these two pieces of information at the feature level by constructing a large feature vector. The problem with feature level fusion/combination is that, during a hazardous situation different behavior changes do not necessarily occur concurrently. Actually, an analysis of the hand-labeled potentially dangerous situations indicated that they are more likely to occur at different timings. Accordingly, an alternative approach which could deal with delayed reactions was devised.

Using detection methods separately, the distortion of each brake and speech frames from clusters (safety model) was calculated, as explained in section III. The detection parameters were set to their optimal values. Then, an 8-second window, set as the duration of a dangerous scene, was shifted concurrently along brake pedal and speech frames. The amplitude of each frame corresponded to the previously calculated distortion from clusters. Inside this 8-second window, frames of each signal with the highest probability of representing a reaction to a hazardous situation, that is, the highest amplitude brake (B_{max}) and speech (S_{max}) frames, were then integrated utilizing (4).

$$\beta B_{max} + (1-\beta) S_{max}. \tag{4}$$

The parameter β is called the fusion factor and ranges from $0 \leq \beta \leq 1$. A zero mean normalization of frames was required in order to have the parameter β favoring both decision methods equally when it was set to 0.5.

Experiments were performed utilizing data divided into three groups, according to their subjective level of dangerousness, as described in section II-B. Consequently, the relationship between drivers' reaction and subject level of dangerousness could be verified. The 8-second window shift was set to 4s, given that this value could not be shorter than the shifts utilized for brake pedal force and speech-based detections. In addition, different values of β were utilized: 0.25, 0.5 and 0.75.

A. Integration-based Detection Results

Best results for group C (high) were achieved with $\beta = 0.25$; for group B (medium) with $\beta = 0.75$; and for group A (low), with $\beta = 1.0$, that is, the brake pedal force-based method. Results are shown in Fig. 7 as ROC graphs, obtained by varying the detection threshold.

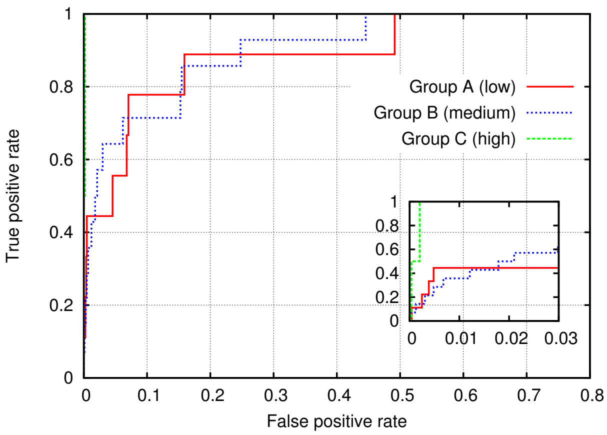

Fig. 7. Best results for the integration-based method utilizing scenes divided according to their subjective level of dangerousness.

VI. Discussion

Results demonstrated that the brake pedal force-based method attained satisfactory results, a true positive rate of 100% for a false positive rate of 4.5%, concernning the detection of 17 scenes where sudden and strong compression of the brake pedal was observed. Results from this work also indicated that future advancements in this area should consider the uniqueness of driving behavior signals for a better retrieval of dangerous situations and for the development of other safety systems. An assistant system which correctly interprets drivers' responses would be far more efficient and interactive than current ones.

In 11 of the 25 hand-labeled scenes, drivers reacted verbally. Reactions could be broadly divided into two groups: high energy words and whispered speech. The division of these two groups was clear in the results. For the detection of these 11 situations, speech-based method obtained a true positive rate of 54% (6 scenes) for a false positive rate of 6.4%. However, in order to detect the other 5 scenes and achieve 100% of detection, a false positive rate of 65% was observed.

Since the speech-based method relied on energy and its dynamics, whispered speech could not be detected. Pitch, formant and timing-related features, effective in detecting emotion from speech and also whispers must be considered for a more efficient detection in further research. Moreover, expletive words uttered during a hazardous situation are often difficult to be recognized, suggesting that a low speech recognition rate is also a promising feature.

As for the integration of sources, the two scenes, which comprised group C (high), were far more easily detected than the others. In this group, drivers reacted intensely with both speech and brake pedal, so the integration method was effective in boosting the detection. For a true positive rate of 100%, a false positive rate of about 0.1% was required for the integration-based method.

In five of the 25 hand-labeled potentially dangerous scenes no substantial reactions from drivers were verified, and in three, drivers only reacted verbally. These situations were divided among groups A and B, what increased the number of false positives for 100% of detection. Group B (medium) was better detected using the integration method, achieving false positive rates of 6.1% and 44.5% for true positive rates of 70% and 100% respectively.

On the other hand, group A (low) was better retrieved by the brake pedal force-based detection method. False positive rates of 7% and 49% were observed for true positive rates of 70% and 100%, respectively. The use of new features concerning vehicle surroundings, such as following distance, and a more efficient speech-based detection are necessary facets to provide both, more accurate hand-labeling and retrieval of all situations.

This research found evidences indicating that further analysis on driving behavior signals processing ought to consider drivers' reactions individuality and the integration of multi-modal responses to hazard. Nevertheless, additional methodology improvements are required, along with a larger number of potentially dangerous scenes. Hence, in this context, future researches will be able to identify the chain of changes in human conduct to better characterize a dangerous situation in vehicle urban traffic. Findings of this study provide a realistic understanding of drivers' responses to a hazardous condition and can be utilized mainly to improve systems that proactively promote safety.

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