

Occupant Classification for an Adaptive Restraint System: The Methodology and Benefits in Terms of Injury Reduction

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Abstract Road traffic injuries kill nearly 1.3 million people annually, so enhancement of traffic safety becomes a high priority for both governmental organizations and automobile manufacturers. In addition to safety measures used to prevent accidents, the improvement of occupant protection by adaptive restraint systems may reduce the effects of traffic accidents more effectively than current passive restraint systems. This study investigates numerically the development of a smart restraint system based on pre-crash classification of occupant posture. A catalog of restraint laws optimized for nine driver postures uniformly distributed in posture space is employed. Performance-based statistical classifiers are developed to recognize the pre-crash posture from the signals of a stereo-vision camera which tracks the driver's head. In addition to a Bayesian approach used frequently in pattern recognition applications, a new classification approach, called Expected Performance Assessment (EPA), was introduced. The performance of the adaptive restraint system with catalog controller (RSC) was investigated using crash simulations with driver on different 200 pre-crash postures. The highest level of injury reduction (28.2 %) compared to the nominal restraint system (RSN) optimized for the nominal posture was obtained using a k-NN classifier and catalog with 8 restraint laws. Improved performance is expected in future studies by expanding the number of restraint laws, experimenting with different restraint parameters, and exploring different sensor signals (features) which may improve classifier accuracy and effectiveness.

Keywords Occupant classification, adaptive restraint system, injury cost

I. INTRODUCTION

Nearly 1.3 million deaths are recorded on the world's roads each year resulting in 20 to 50 million people injured [1]. In addition, it has been estimated that unless immediate action is taken, by 2030 the number of fatalities will almost double and the road fatalities will rise from the ninth to fifth leading cause of death in the world [1]. Hence, enhancement of traffic safety becomes a high priority for both world and governmental organizations, and automobile manufacturers [1].

Safety measures corresponding to the three phases of a traffic accident: pre-crash, crash, and post-crash are classified as a) accident avoidance, b) occupant protection, and c) rescue, respectively. Recent advancement in sensor technology induced a significant development of collision avoidance systems [2-3] such as warning systems (e.g. lane departure, forward collision, etc.), assistance systems (e.g. brake assist, traction control devices, adaptive cruise control, lane keeping assist etc.), and automatic safety systems (e.g. emergency braking, etc.). While the numbers of injury-related traffic accidents are still high (2.12 million in US [4], 1.3 million in EU [5]), the worldwide vehicle safety experts agree that current safety systems for occupant protection should be improved.

While current legislative and consumer standards typically assess the injury risk of an average size Anthropometric Test Device (ATD) in a standard posture with a limited range of impact conditions, the risks of occupant injuries depend on many potential variables related to the crash and occupant conditions. To manage these wide variations of impact conditions encountered in vehicle accidents, "smart" (also known as "adaptive",

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“active”, or “intelligent”) restraint systems which adapt to the specific conditions have been researched [6-10]. Several adaptive systems were developed assuming the occupant, restraint systems, vehicle interior components and their interaction can be represented accurately by a linear time invariant (LTI) system (design model). The variable parameters of the restraint systems (e.g. belt force) and injury criteria are correlated with input and output variables of the LTI system [8-10]. While some promising results were proved by numerical simulations, these systems require complex sensors which have to measure and then to calculate injury criteria (e.g. thoracic criteria) in real time.

Current study introduces a novel adaptive restraint system which uses data mining techniques to select the best restraint system from a pre-calculated “look-up” table in order to reduce the injury cost for a specific driver in a certain frontal crash. While the benefit of the novel approach is proved only for the recognition of the driver’s pre-crash posture, the method could be extended to more occupant and collision variables.

II. METHODS

The concept of an adaptive restraint system with a look-up catalog controller

During a collision, the restraint system components (e.g. seat belts and air bags) try to reduce the contact forces between the passenger and the vehicle interior or restraint system below the tolerance levels corresponding to passenger biometrics [11-12]. The primary metric governing the optimization is the degree of injury sustained by the vehicle's passengers in the event of a collision. Assessment of injury cost is most commonly done in economic terms which include cost of medical treatment as well as long-term rehabilitation and disability costs. These costs are estimated by calculating injury metrics from crash simulations and then using the corresponding injury risk curves to determine the probability of the severity of injury (i.e. AIS level). The whole body injury metric (WBIM) developed previously [11-12] based on the injury metrics corresponding to head (HIC), neck (N_{ij}), chest (deflection), and femur/ leg (axial load) were used in current study to estimate the injury cost in a crash simulation. While the injury cost has clear advantages with respect to other optimization parameters by including all medical, rehabilitation, and disability costs into one parameter, its formulation is not world-wide standardized. New vehicles are continuously being equipped with more sensors that can detect information related to characterizing the dynamic behavior of the vehicle in a collision (e.g. linear and angular accelerometers, crush zone sensors, rate of approach sensors) and the passenger (e.g. seat load cells, ultrasonic/infrared sensors, cameras, seatbelt payout sensors, seat position sensors) [13]. Logically, these sensor signals can be processed and utilized in statistical models to classify occupants and collision types (Fig.1) [14-15].

Assuming the passenger and collision properties can be determined, a restraint design can be found to minimize the injury metric. Generally, this optimization problem is non-convex and very time-consuming [12]. A restraint model that generates a database “off-line” which then can be efficiently mined in real time to obtain near-optimal control law selection during a crash event is proposed in this study [12, 16]. This selection process could be done either in the pre-collision phase (based on information received from active safety devices) or at the beginning of the collision phase such that there is sufficient times to analyze the sensor signals and implement the proper restraint laws. The benefits of the adaptive restraint system could be evaluated numerically by calculating the injury cost associated with implementing a) a restraint system with a catalog controller (RSC) and b) a restraint system with a nominal restraint law (RSN) optimized for the standard posture [12](Fig.1).

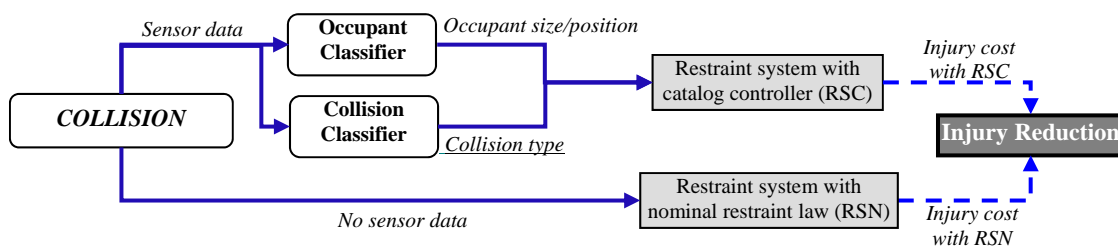


Fig.1. Schematic flow of the methodology used to develop and validate a restraint system with a catalog controller.

While the methodology presented here could be applied to classify both the occupant and the collision type, this study focuses on identifying the position of the occupant and assumes the collision type and occupant anthropometry constant and known. The collision type chosen was a typical 57 km/h deceleration pulse corresponding to a frontal crash of a mid-size vehicle [12].

Posture Recognition during a Collision

Previous studies [11] have shown that occupant posture during pre-collision phase has a significant effect (35%) on injury outcome. In our recent study [12], posture parameters were varied in a statistical/parametric study to determine which were significant with respect to injury. The lumbar flexion and sideways flexion (Fig.1) showed to be the most significant posture parameters of the occupant facet model (50th percentile male – MADYMO-) in terms of injury cost (WBIM) from a set of parameters which also included the neck flexion and seating position [12]. The x and y components of the head-to-camera distance (Fig. 2 a) showed to be the highest correlated signals with respect to the most significant posture variables from a set of possible sensors, thus these signals were used as features in the pattern recognition algorithms.

Acknowledging that it may be impossible to optimize a restraint law for all pre-crash scenarios (infinite posture space), the occupant space was divided into nine posture classes (Fig. 2b) defined based on head location [12]. Then, the restraint parameters were optimized in terms of minimizing injury cost for pre-crash postures corresponding to the centers of the nine regions. These optimized restraint laws were included in a “look-up” table (the catalog controller).

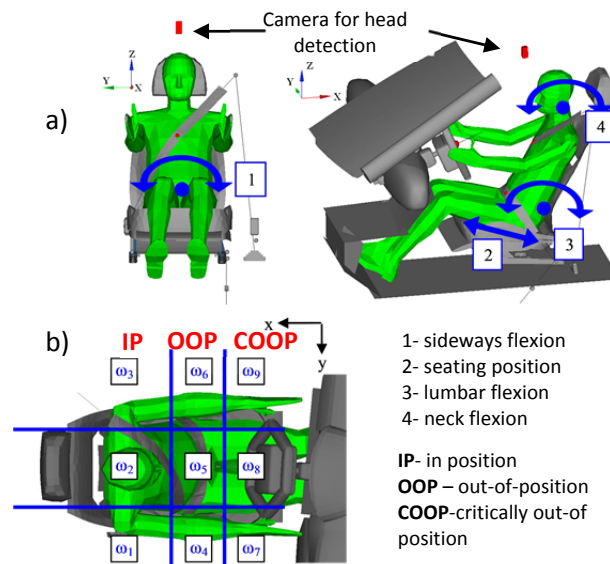


Fig.2. a) Posture variables, b) Posture classes defined based on head location [12].

Bayesian Classification

A Bayes classifier is a pattern recognition algorithm that classifies objects using Bayes’ decision theory and requires two conditions: 1) a cost can be associated with the damage involved when an object is misclassified and 2) the expectation of cost is acceptable as an optimization criterion. Suppose there is an arbitrary classifier that asserts a class ω_j (from the set of classes $\Omega = \{\omega_1, \dots, \omega_K\}$, where K is the number of classes) to a measurement vector \mathbf{x} coming from a true class ω_i . Associated with this assertion is a cost $C(\omega_j | \omega_i)$ and a posterior probability $P(\omega_i | \mathbf{x})$ of having an object of class ω_i given the measurement vector \mathbf{x} . The measurement vector \mathbf{x} , also called the feature vector, describes the significant features of an object that will differ from class to class, but also vary within the same class. The expectation of the cost, also known as the conditional risk $R(\omega_j | \mathbf{x})$, is

$$R(\omega_j | \mathbf{x}) = \sum_{i=1}^K C(\omega_j | \omega_i) P(\omega_i | \mathbf{x}) \tag{1}$$

where the posterior probability can be written as

$$P(\omega_i|\mathbf{x}) = \frac{p(\mathbf{x}|\omega_i)P(\omega_i)}{P(\mathbf{x})} \quad (2)$$

The conditional probability density function (PDF) of class ω_i $p(\mathbf{x}|\omega_i)$ describes the distribution of feature vectors in the feature space inside a particular class. The prior probability $P(\omega_i)$ is based on previous knowledge about the classes independent of the feature vector. The divisor $P(\mathbf{x}) = \sum_{i=1}^K p(\mathbf{x}|\omega_i)P(\omega_i)$ is a scaling factor which assures that the sum of the posterior probabilities is equal to 1. In this study, the feature vector \mathbf{x} consisted of the sensor signals that had the highest correlation with the significant posture variables (i.e. camera-to-head distance had the highest correlation with lumbar and sideways flexion [12]). Since the classes are formulated in this study, it was assumed there is no prior knowledge about the classes, so $P(\omega_i) = 1/K$ for $i=1...K$.

The decision principle behind Bayes' decision theory is to choose the class ω_j that minimizes the overall (conditional) risk, so the Bayes minimum risk (BMR) classifier is derived as [17]:

$$\varphi_{BMR}(\mathbf{x}) = \operatorname{argmin}_j [\sum_{i=1}^K C(\omega_j|\omega_i)p(\mathbf{x}|\omega_i)] \quad (3)$$

A simplified Bayesian classifier, called minimum error rate (MER) classifier, is obtained if a uniform cost function is assumed. In this case, a unit cost is assumed when an object is misclassified and zero cost when the classification is correct, which simplifies to [17]:

$$\varphi_{BMR}(\mathbf{x}) = \operatorname{argmin}_j [p(\mathbf{x}|\omega_i)] \quad (4)$$

The main challenge in developing Bayes classifiers is typically determining the conditional PDFs $p(\mathbf{x}|\omega_i)$. While the conditional PDFs of the posture classes are usually unknown, supervised parametric (SPL) and nonparametric learning (SNL) methods are used to approximate them. The SPL techniques assume the expressions of the probability densities and estimate their unknown parameters using a training set. The SNL approach also uses a training set to determine the conditional probability distributions, but without prior knowledge of their functional form [12, 16]).

Posture Recognition using Region-based Classification

A Bayesian approach was applied in our previous study [12], where the posture space was divided into nine regions/classes based on the head position (feature). Two Bayesian parametric classifiers (MER and BMR) with an estimated Gaussian PDF were developed to assign a class for to unknown postures based on sensor data provided by a stereo-vision camera (Fig.2). The evaluation of the classifiers on an independent validation set (a Sobol DOE with 200 postures) showed a maximum average reduction of injury cost of 21% (MER classifier) compared to a restraint system optimized in the standard posture (used currently in regulations).

To investigate the global performance of the nine restraint laws included in the catalog, a uniform grid of 196 points (14x14) was selected in the posture space defined by the angles of lumbar and sideways flexion. The lumbar flexion angle was varied uniformly from -3.5° to 35.6° and the sideways flexion angle was varied from -14.4° to 14.4° (Fig. 3a). In this training set neck flexion and seating position were kept constant to reduce the noise in the sensor signals. Crash simulations were run in MADYMO™ v7.2 (TNO MADYMO BV., Netherlands) with the occupant in the pre-crash postures corresponding to these grid points for each of nine catalog restraint laws and the nominal restraint law. The normalized injury cost was calculated for each of the crash simulations and sensor signals were extracted to be used later in the classifiers.

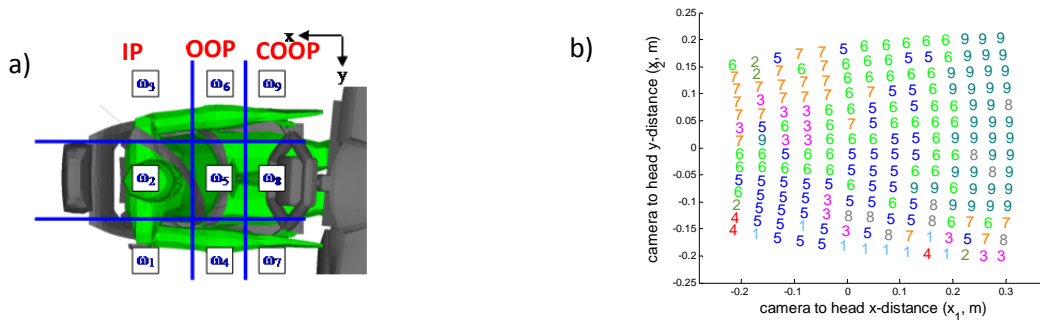


Fig 3. a) The region-based posture classes b) best restraint laws at 196 uniformly distributed postures in the occupant posture space defined by lumbar flexion and sideways flexion angles

The performance evaluation of nine controllers on a uniform grid of the posture space showed a non-uniform distribution of the best controller (Fig. 3.b) which showed hyper-optimality in the controllers. The assumption that the restraint laws will be best throughout their respective region/class was proved to be false. Restraint laws 5, 6, and 9 are the best laws for more than half of the posture space (69.4%), and the most sensitive restraint laws (i.e., 2, 4, 8) occur only at a few points (8.2%). The poor performance of restraint laws 1, 2, 3, 4, and 7 with respect to their regions may be due to the fact that a local minimum was reached in the restraint parameter design space or a point of hyper optimality was achieved such that the performance decreased significantly when the posture was varied slightly. In addition, the results show that it may not be necessary to include all nine laws when forming the RSC since the sensitive restraint laws are rarely the best restraint law over the entire posture space. In conclusion, it is clear that more improvements in terms of injury reduction can be obtained by improving the selection process of controllers.

Posture Recognition using Performance-based Classification

The sensitivity in performance of several restraint laws optimized in certain points of the posture space showed that improved results may be achieved if a performance-based classification was implemented rather than a region-based classification. Two approaches were tested for development of performance-based classifiers: 1) the classical Bayesian approach [17] 2) a novel approach called Expected Performance Approach (EPA).

A. Bayesian Approach

As mentioned before, in the Bayesian approach a restraint law is assigned to each class. While in the region-based approach a class was predefined around the posture point used to optimize the restraint laws, the classes of the performance-based classifiers were defined based on their best performance calculated in the 196 uniformly distributed postures in the occupant space. Both parametric and non-parametric supervised learning classifiers were tested. While short descriptions of these statistical classifiers employed in this study are briefly outlined below, the reader is referred to Duda et al. [14] or van der Heijden et al. [17] for a more detailed treatment of pattern recognitions algorithms.

1) Supervised parametric learning (SPL) classifiers

The SPL classification methods used in this study were linear and quadratic discriminant classifiers (LDC and QDC, respectively). QDC assumes that the measurement vectors coming from an object of class ω_k are normally distributed with mean vector μ_k and covariance matrix C_k . In the simple case where the length of the measurement vector is 2 (two feature case), the decision boundaries dividing classes are quadratic. LDC is a simplification of the quadratic classifier which assumes that the covariance matrices do not depend on the classes (i.e. $C_k = constant$). In LDC case, the decision boundaries in the two feature case are linear [17].

2) Supervised non-parametric learning (SNL) classifiers

SNL classifiers are much more general than SPL classifiers, but they require larger training sets to obtain accurate results. The SNL classifiers used in this study were Support Vector Machine (SVM), Parzen (PARZ), and nearest neighbor (NN) classifiers.

SVM classifier is a nonlinear classifier that forms decision boundaries by maximizing the margin between two different classes (i.e. the distance between samples that can be drawn around the decision boundary). To develop the algorithm for this classifier, a linear classifier described as $g(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b$ is used with training samples \mathbf{x}_n , $n = 1, \dots, N$ (where N is the number of samples) [17]. Maximizing the separation boundary is equivalent with minimizing $\|\mathbf{w}\|^2$ and it is solved using standard software packages. To increase generality of the SVM classifier, the boundaries can be changed from linear to nonlinear using a method known as the "kernel trick". In this case, the inner product between the measurement vectors (x_m, x_n) are replaced by a more general kernel function $K(x_m, x_n)$. In this study, two kernel functions were selected, a radial basis function (referred to as SVM_r)

$$K(x_m, x_n) = e^{-\|x_m - x_n\|^2 / \sigma^2} \tag{5}$$

and a polynomial function (referred to as SVM_p).

$$K(x_m, x_n) = (x_m^T x_n + 1)^p \tag{6}$$

The width of the radial basis function σ and the degree of the polynomial function p were optimized using the cross-validation method. The cross-validation method partitions the training set into Y equally sized subsets. A classifier is constructed by leaving out one of the Y subsets and then the rest of the subsets are used for training. The subset not in the training set is used as validation data and an estimate is calculated. This is done for all subsets and then the estimates are averaged in order to find an estimated error rate. A special case of the cross-validation method divides the training set into the smallest subsets possible (i.e. $Y =$ the number of samples). This gives the best estimate of the error rate and is known as the leave-one-out method [17]

To apply SVM in the case where the number of classes is greater than two, a classifier for each class must be developed using the one-against-rest strategy where all other classes are assumed to be one class. The two-class classifiers are then combined to properly identify objects over all classes.

The algorithm for the Parzen classifier is obtained by replacing the conditional probability density function with the Parzen estimation $\hat{p}(x|\omega_k)$ in the equation of the general Bayes classifier (eq. 4)

$$\phi_{PARZ}(\mathbf{x}) = \operatorname{argmin}_j [\hat{p}(\mathbf{x}|\omega_i) \hat{P}(\omega_i)] \tag{7}$$

The Parzen estimation approximates the conditional probability density functions $\hat{p}(\mathbf{x}|\omega_k)$ by considering separately each the training subsets T_k for each class ω_k [17]. The probability is assumed to have a maximum at the point in the measurement space where the training measurement vector \mathbf{x}_j is located. Then, the probability is assumed to decrease as the distance $\rho(\mathbf{x}, \mathbf{x}_j)$ increase from \mathbf{x}_j as less is known about the class of the measurement vector. This is done for all measurement vectors N_k in a given class ω_k . The kernel functions for all of the measurement vectors are then summed and normalized to attain an estimate for the conditional density.

$$\hat{p}(\mathbf{x}|\omega_k) = \frac{1}{N_k} \sum_{\mathbf{x}_j \in T_k} \hat{h}(\rho(\mathbf{x}, \mathbf{x}_j)) \tag{8}$$

where a kernel function $\hat{h}(\rho(\mathbf{x}, \mathbf{x}_j))$ has a maximum at $\mathbf{x} = \mathbf{x}_j$, monotonically decrease as $\rho(\mathbf{x}, \mathbf{x}_j)$ increases, and is normalized over the entire space.

Nearest neighbor classification uses a special technique that classifies objects without explicitly estimating probability densities [17]. The identification of an object using this method considers a hyper-sphere with dimension equal to the length of the measurement vector where the center is the test sample in question. The volume of this hyper-sphere is denoted as $V(\mathbf{x})$. The radius of the sphere is selected to surround K number of samples out of the total number of samples in the training set N_K . Using this information, an estimate of each class density is given by

$$\hat{p}(\mathbf{x}|\omega_j) = \frac{K_j}{N_j V(\mathbf{x})} \tag{9}$$

where K_j is the number of samples out of the K nearest neighbors for ω_j . The prior probability for each class can be estimated using

$$\hat{P}(\omega_j) = \frac{N_j}{N_K} \tag{10}$$

Using the Bayes framework, the asserted class can be found by substituting Equations (9) and (10) into Equation

(4). Eliminating $V(\mathbf{x})$ and N_k since they do not depend on j and simplifying the equation results in

$$\phi_{KNN}(\mathbf{x}) = \operatorname{argmin}_j [\hat{p}(\mathbf{x}|\omega_i)P(\omega_i)] = \operatorname{argmin}_j [K_j] \quad (11)$$

Thus, the decision algorithm simplifies to asserting the class that has the most samples out of the K nearest neighbors considered [17]. For this study, K was optimized for each optimum catalog combination using the leave-one-out method.

B. Expected Performance Assessment (EPA) Approach

The Expected Performance Assessment (EPA) approach, developed in this study, has many similarities with the Bayes classifiers, but is more general as it does not assign a particular restraint law to a certain class. This allows for an infinite number of restraint laws to be considered rather than being limited by the number of classes as long as the restraint law performance for each is determined for each training point. The classifier evaluates the performance of each restraint law over the entire training set posture region by a cost function (i.e. $C_{EPA}(OP_i, RL_j)$, where OP_i is the occupant posture and RL_j is the restraint law) taking into consideration the proximity of the points (i.e. $D_i(\mathbf{x})$) with respect to the test point being identified. The restraint law with the minimum cost risk is then chosen. The cost function for the EPA classifier is formulated using the WBIM values with size $N_K \times N_{RL}$, where N_{RL} is the number of restraint laws in the RSC catalog (in our case $N_K=196$ and $N_{RL}=9$). The proximity of the points with respect to the test point is quantified by calculating the Euclidean distance to each training set point. The decision rule for the EPA classifier is defined as follows

$$\phi_{EPA}(\mathbf{x}) = \operatorname{argmin}_j \left[\sum_{i=1}^{N_K} D_i(\mathbf{x}) C_{EPA}(Post_i, RL_j) \right] \quad (12)$$

where

$$D_i(\mathbf{x}) = \frac{1}{\sum_{l=1}^L (x_l - x)^2} \quad (13)$$

Performance of RSC with a reduced catalog

The development of a RSC with less restraint laws may simplify the development of accurate classifiers and may result in a reduced production cost. In addition, it would be interesting to examine how the performance of the restraint system varies relative to the number of restraint laws. A balance must be found between minimizing the number of restraint laws N_{RL} and maximizing the injury reduction across the entire posture. The best restraint law combination for each N_{RL} number of restraint laws (from 1 to 9) was determined. All possible combinations of the restraint laws $\left(\frac{9!}{N_{RL}!(9-N_{RL}!)}\right)$ for a certain number of restraint laws (N_{RL}) were generated, and the corresponding simulations were performed. The overall average injury reduction (compared to RSN in the 196 posture set described previously) for all cases was then calculated (eq. 14).

Training and testing the performance-based classifiers

The classifiers were trained based on the sensor data recorded in the 196 postures evaluated previously (Fig. 3c). The performance of the restraint systems with catalog controllers (RSC) and statistical classifiers were evaluated using a validation set which contains postures which were not included in the training set. The validation test was created by generating a 200 Sobol DOE of postures varying lumbar and sideways flexion with the same range as the training set.

Crash simulations were performed with the occupant in all postures corresponding to both validation sets (1 and 2) and using all $k=9$ restraint laws included in the catalog and the nominal restraint laws. The optimal injury reduction with respect to nominal restraint law was defined as the maximum injury reduction which can be obtained for the pre-crash posture ω_i :

$$IR_{opt, \omega_i} = \max_{k=1,10} \left[\left(\frac{inj_{RSN, \omega_i} - inj_{k, \omega_i}}{inj_{RSN, \omega_i}} \right) \times 100 \right] \quad (14)$$

where inj_{k, ω_i} and inj_{RSN, ω_i} are the injury costs recorded with restraint law k and nominal restraint, respectively.

III. RESULTS

The maximum performance of the RSC system with reduced number of restraint laws

The best restraint law combinations were recorded and their percentage breakdown were reported (Table I). It can be seen that the average injury cost can be reduced by 20.9% with respect to the nominal restraint law and training set test points if only restraint law 6 is implemented. The reduction of injury increases as the number of restraint laws increases, but the performance of the catalog controller decreases due to the nonlinear relationship of the number of restraint laws and the average injury reduction (98% of the injury reduction obtained by 9 RLs can be realized by using only 5 RLs). As seen by Table I, the last 4 RLs added to the catalog only account for approximately 13% of the posture space. To assign a certain restraint law based on the coordinate of driver’s head recorded by the stereo-vision camera in a certain crash scenario, classifiers should be developed for each RSC system.

TABLE I
OPTIMUM CATALOG COMBINATIONS AND THEIR CORRESPONDING OVERALL INJURY REDUCTION

Nr. RL	Percentage (%) each RL produces minimum injury cost									Ovr. Inj. Red. (%)
	RL 1	RL 2	RL 3	RL 4	RL 5	RL 6	RL 7	RL 8	RL 9	
1						100				20.9
2					39	61				25.5
3					38	38			23	27.4
4					34	29	15		22	28.4
5	6				29	29	14		21	29.1
6	6		7		26	28	13		21	29.4
7	5		7		24	27	12	6	19	29.6
8	5	2	7		24	27	12	5	19	29.7
9	4	2	7	2	23	27	12	5	19	29.7

Contour plots showing the normalized injury costs over the whole posture space for both RSN and RSC systems are illustrated in Figure 4. It can be seen that the occupant is at a lower risk of injury leaning left and is more prone to injury if leaning forward and to the right. The RSC system reduces significantly the injury cost with respect to RSN system in the majority of the posture space regions. Lower performance was observed in a few postures corresponding to the leaning right region (in position and out-of-position) which may be improved by adding several restraint laws optimized for these regions in the catalog.

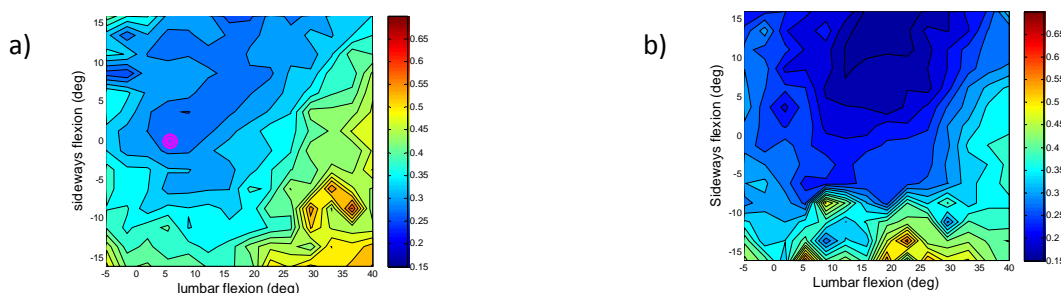


Fig.4. The contour plot of injury cost for a) nominal RSN system b) an ideal RSC with nine restraint laws included in catalog

The RSC system with performance-based classifiers

An example of the class boundaries of the four-class classifiers determined using the training set is presented (Fig. 5). LDC is the simplest classifier and produces linear boundaries separating the different classes. QDC and SVM_p show relatively similar nonlinear boundaries and divide the posture class into distinct convex classes. Complex boundaries which result in concave and non-distinct posture classes are determined by SVM_r and Parzen classifiers. k-NN and EPA are the most complex classifiers as the boundaries fit the training data very closely which produced multiple regions for RLs 5 and 6.

The performance of the posture classifiers varies with respect to number of restraint laws, classifier type and validation set. For validation set 1 (Table II), the PARZ classifiers showed the highest performance for a reduced number of restraint laws (up to 3), but their performance slightly decrease as the number of restraint laws increases. The k-NN classifiers showed a monotonically increased performance with respect of the number of restraint laws and the highest performance among all classifiers for more than 3 restraint laws. The EPA showed a good performance being usually one of the best three classifiers.

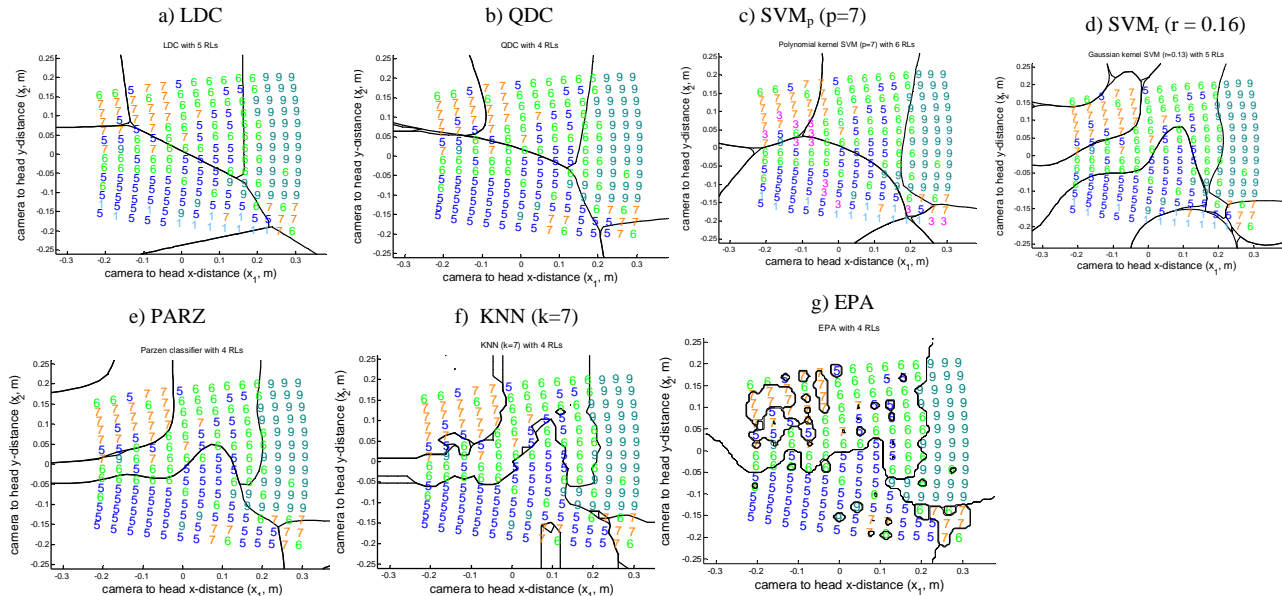


Fig.5. Example showing the class boundaries using a) LDC, b) QDC, c) SVM_p, d) SVM_r, e) PARZ, f) k-NN and g)EPA for the four-class case

TABLE II

OVERALL INJURY REDUCTION FOR OPTIMUM PERFORMANCE AND CLASSIFIERS WITH REDUCED NUMBERS OF RLS (NOTE: THE BEST CLASSIFIERS FOR A CERTAIN NUMBER OF RESTRAINTS IS UNDERLINED)

Classifier	Percentage (%) each RL produces minimum injury cost							
	RL 2	RL 3	RL 4	RL 5	RL 6	RL 7	RL 8	RL 9
LDC	24.4	25.5	25.6	25.6	25.7	26.1	26	26
QDC	24.7	25.7	26.0	25.9	25.9	26.4	26.3	26.4
SVM _p	25.1	26.0	26.3	26.4	26.7	25.8	25.4	25.5
SVM _r	25.2	26.5	26.8	<u>27.9</u>	27.5	26.2	26.5	26.8
PARZ	<u>25.3</u>	<u>26.55</u>	27.0	27.4	27.6	27.4	27.5	26.4
k-NN	24.9	26.4	<u>27.3</u>	27.8	<u>27.9</u>	<u>28.1</u>	<u>28.2</u>	<u>28.0</u>
EPA	24.8	26.2	26.6	27.2	27.3	27.2	26.9	26.9
OPT	26.0	27.7	28.8	29.6	30.1	30.2	30.3	30.4

Note: the lowest computational time for each N_{RL} was underlined.

TABLE III
COMPUTATIONAL TIME* (μ s) FOR THE CLASSIFIERS

Classifier	Number of restraint laws used								
	RL 2	RL 3	RL 4	RL 5	RL 6	RL 7	RL 8	RL 9	
LNC	13	15	16	16	17	18	18	19	
QNC	14	15	16	16	17	18	19	20	
SVM _p	64	232	375	370	426	491	676	711	
SVM _r	59	230	288	353	425	481	553	607	
PARZ	60	79	94	118	135	150	164	183	
k-NN	41	42	41	42	42	42	42	43	
EPA	<u>12</u>	<u>12</u>	<u>11</u>	<u>12</u>	<u>12</u>	<u>12</u>	<u>12</u>	<u>13</u>	

* – the computational time recorded on an Intel Core2Quad 2.4 GHz processor Q6600, 8 GB DDR2 RAM
Note: the lowest computational time for each N_{RL} was underlined.

The computational time for all classifiers is displayed in Table 3. EPA had the lowest computational time and did not vary with respect to N_{RL}. LNC, QNC, 1NN, and KNN had slightly longer computational times and increased slightly as N_{RL} increased. The computational time of PARZ also increased as increased but took longer due to the estimated conditional probability density functions. SVM_p and SVM_r showed an increase in computational time due to the fact that the number of classifiers was equal to N_{RL}.

IV. DISCUSSION

Restraint systems are key factors in preventing and reducing occupant injuries when a crash cannot be avoided. Optimizing the parameters of these systems for a certain crash scenario is typically a non-trivial and time-consuming problem due to the large number of collision variables involved. The target of fixed optimization design of current restraint systems is generally aimed at “typical” passengers (50th percentile male) in a “typical” pre-crash posture (relaxed posture) involved in a “typical” collision (e.g. frontal collision with a 56 km/h initial velocity [18]). The performance of a restraint system obtained by this fixed optimization approach showed a significant sensitivity when the occupant pre-crash posture was varied (Fig. 4a). A crash simulation study with volunteers [19] reported that only 17% of passengers were close to nominal posture during pre-crash phase; therefore, these results may highlight the need for adaptive restraint systems which takes into account occupant and vehicle characteristics (Fig. 4b).

The novel restraint approach proposed in this study includes a statistical classifier which can recognize the posture of an occupant using sensor data and select an appropriate restraint law for the specific conditions of a crash from a set of restraint laws included in a predefined “look-up” table. A Bayesian approach was employed to develop six classifiers using both parametric learning (LDC, QNC) and non-parametric learning (SVM_p, SVM_r, PARZ, kNN) methods. A usual approach in the safety field is to divide the occupant space in sub-space (regions) and use them in the occupant classification process. This approach was used in our previous study [12] which developed two SPL classifiers (error rate and minimum risk classifiers) and showed a maximum 21% overall injury reduction compared to the nominal restraint system.

In current study, a performance-based approach was used to develop the nine Bayesian classes using the results of crash simulations performed with all restraint laws and 196 distinct postures uniformly distributed in the posture space. The performance of the RSC showed to be sensitive to the type of the classifier and to the number of restraint laws used. Overall, the injury reduction of performance-based classifiers was between 24.4 % and 28.2 %, significantly higher than the highest injury reduction obtained using region-based classifiers.

The EPA approach was proposed and used in this study. This novel approach has many similarities with Bayesian supervised learning, but it is more general and more computational efficient (about 12 μ s computational time). While the number of restraint laws included in the catalog of a Bayesian classifier should be equal with the number of classes, the EPA classifiers does not have this constraint. Therefore, the performance of the EPA classifiers could be improved by adding more restraint laws into its catalog. Other distance measures in the decision rule, different than the Euclidian norm used in our current study, may also yield better performance for EPA classifiers than the classical Bayesian classifiers in the real-time optimization process.

A limitation of this study was the fact that the number of restraint laws was restricted to the nine developed in the previous study [12]. The performance of RSC can be improved by adding more possible restraint laws and optimizing more restraint parameters (e.g. pretensioner stroke, etc.). However, a challenging question would be choosing the best approach to attain these restraint laws (e.g. point-optimization, a region-optimization, simply choosing some parametric restraint laws in the restraint space (without optimization), etc). It is believed that more research in this field is needed to determine the optimum approach. In addition, higher injury reduction percentages may be possible by including other occupant characteristics in the classification process (e.g. age, sex, and anthropometric data) and combining them with the crash characteristics (the current study only employed 50th male occupants and full frontal crashes at 56 kmh initial velocity).

V. CONCLUSIONS

This study investigated numerically the development of an adaptive restraint system that selects from a catalog the most appropriate restraint law corresponding to the occupant's pre-crash posture. A catalog of nine restraint laws optimized in a previous study [12] for postures that were uniformly distributed in posture space was employed. The performance of these restraint laws optimized locally showed significant sensitivity when they were evaluated over the entire posture space. While the restraint laws corresponding to the center and leaning left OOP region showed the best global performance, the restraint law corresponding to the leaning right OOP region recorded the worst performance. For an ideal RSC with all nine restraint laws applied to the validation set, the potential injury reduction was up to 30.4% with respect to the RSN.

This study proved that the definition of the posture classes plays a major role in obtaining a good performance in reduction of occupant injury cost during the crash. The best RSC with two posture classes defined based on performance showed a significantly better injury reduction than a RSC with nine uniform classes developed in our previous study. Improved performance is expected in future studies by expanding the number of restraint laws the catalogs of EPA classifiers, experimenting with different restraint parameters, and exploring different sensor signals (features) that more clearly define restraint law boundaries thus improving classifier accuracy and effectiveness

VI. REFERENCES

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