Performance-Based Classification of Occupant Posture to Reduce the Risk of Injury in a Collision

Costin D. Untaroiu and Thomas J. Adam

Abstract—This study numerically investigates the development of an adaptive restraint system based on precrash classification of occupant posture. A catalog of restraint laws optimized for nine postures uniformly distributed in posture space is employed. First, the performance of each restraint law is globally assessed by performing crash simulations in a parametric fashion throughout the entire posture space. Then, restraint systems with catalogs (RSCs) with various numbers of restraint laws are evaluated in terms of injury cost with respect to a restraint system optimized with respect to a nominal posture (RSN). Parametric and non-parametric supervised classifiers are developed for each catalog, and their performances are analyzed. A catalog with the optimized laws of two out-of-position postures (central and leaning left) showed high performance in terms of reduced injury cost with respect to optimum performance for two distinct validation sets (25.3%/21.6% with statistical classifiers versus 26%/23.8% optimum performance). The percent injury reduction increased as the number of classes was increased but had diminishing returns going from five to nine restraint laws (28%/24.2% with statistical classifiers versus 30.4%/29.1% optimum reduction). The results of this study indicated that restraint systems with performance-based classes perform better than restraint systems with region-based classes. Expanding the number of restraint laws and developing new classification algorithms may further improve the performance of adaptive restraint systems.

Index Terms—Adaptive systems, intelligent vehicles, numerical simulation, vehicle safety.

I. INTRODUCTION

The invention of automobiles has led to personal mobility, which has changed the lives of individuals during the 20th and 21st centuries. However, the growth of automobile usage has led to a dramatic increase in traffic injuries and fatalities. 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 road fatalities will rise from the ninth to the fifth leading cause of death in the world [1]. Hence, enhancement of traffic safety has become a high priority for world and governmental organizations and automobile manufacturers [1].

Safety measures corresponding to the three phases of a traffic accident, namely, precrash, crash, and postcrash, are classified as 1) accident avoidance, 2) occupant protection, and 3) rescue, respectively. Recent advancement in sensor technology has induced significant development in collision avoidance systems [2]–[10] such as warning systems (e.g., lane departure and forward collision), assistance systems (e.g., brake assist, traction control devices, adaptive cruise control, and lane keeping assist), and automatic safety systems (e.g., emergency braking). While the number of injury-related traffic accidents is still high (2.12 million in the United States [11]; 1.3 million in the European Union [12]), worldwide, vehicle safety experts agree that current safety systems for occupant protection should be improved.

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. However, the risks of occupant injuries depend on many potential variables related to the crash conditions (e.g., speed and crash direction), vehicle properties (e.g., interior parts and restraint system), and occupant characteristics (e.g., anthropometry and posture). To manage these wide variations of impact conditions encountered in vehicle accidents, “adaptive” (also known as “smart,” “active,” or “intelligent”) restraint systems that adapt to the specific conditions have been researched [13]–[17]. The difficulty in designing these systems is identifying and then incorporating occupant variables (e.g., occupant weight, seating position, and safety-belt usage) and vehicle variables (e.g., crash deceleration pulse) almost instantaneously into control restraint parameters to optimally protect the occupant.

Two types of “adaptive” restraint systems were proposed in the literature: 1) Continuous Restraint Systems (CRS), in which restraint settings can be continuously changed during the crash, and 2) Fixed Restraint Systems (FRS), in which the type of crash and occupant are classified before the crash, and the most appropriate restraint parameters included in a finite set are applied during the crash. CRS systems are developed assuming that the occupant, restraint systems, vehicle interior components, and their interaction can be accurately represented 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. The design models were initially represented by a 1-D model (two lumped masses [18] and, more recently, by 2-D models with three masses [19] and 11 masses [17]). While these CRS systems showed promising numerical results [17] by controlling the chest acceleration of a simplified Hybrid III model in a nominal posture (relaxed posture), their development is still at the theoretical level and focused only...
on control of the belt. In addition to the fact that CRS systems require complex sensors that have to measure and then calculate injury criteria (e.g., thoracic criteria) in real time [17], their design required two contradictory factors: 1) accuracy that requires higher complexity and 2) computational efficiency (to be real-time controlled) that requires less complexity. Several FRS systems have been already implemented in current restraint systems, specifically for airbag systems triggered by occupant classifiers [20], but the development of the adaptive FRS systems is still in an incipient phase.

II. MOTIVATION

During a collision, the restraint system components (e.g., seat belts and airbags) try to reduce the contact forces between the passenger and the vehicle interior or restraint system below the tolerance levels corresponding to passenger biometrics [21]. Conceptually, the problem of restraint system optimization is relatively easy to describe. The primary metric governing the optimization is the degree of injury sustained by vehicle occupants in the event of a collision. Assessment of injury is most commonly quantified in terms of medical, rehabilitation, and disability costs [21]. The actual value of the metric depends on the specific injuries (type and severity) incurred during the collision and is determined by a complex combination of factors such as 1) passenger properties (precrash posture, size, weight, age, gender, etc.), 2) collision properties (relative speed, direction, offset, etc.), 3) vehicle properties (interior geometry/material, crush zone properties, etc.), and 4) restraint properties (airbags, pretensioners, force limiters, firing algorithms, etc.). Previous studies [22] have shown that occupant posture during precollision phase has a significant effect (35%) on injury outcome. In our previous study [21] and in the current study, the vehicle and occupant characteristics are constant and assumed to be known, whereas the posture of the occupant is varied and unknown. The design/control optimization objective is to minimize the injury metric (cost) by defining a restraint law tailored to a specific occupant precrash posture. In our recent studies [21], [22], the performance of adaptive restraint systems has been evaluated based on a whole body injury metric (WBIM), which takes into account injury risk curves for several body regions and weighs the probabilities based on estimated US medical costs associated with the severity of the injury. Posture parameters were varied in a statistical/parametric study to determine their influence on crash injuries. The lumbar flexion and sideways rotation [see Fig. 1(a)] were found to be the most significant posture parameters of the occupant facet model (50th male—MADYMO) in terms of injury cost (WBIM) from a set of parameters that also included the neck flexion and seating position [21]. Out of a set of possible sensors, the $x$ and $y$ components of the head-to-camera distance were the highest correlated signals with respect to lumbar and sideways flexion. Thus, these signals were used as “features” in the pattern recognition algorithms.

The occupant space was discretized into nine posture classes defined based on head location [21] [see Fig. 1(b)]. Two Bayesian classifiers were trained using the camera-to-head signals recorded from a set of 500 postures selected using a Sobol design of experiment (DOE). The parameters of the restraint system optimized for the nine postures located at the center of each posture class were included in a catalog (see the Appendix).

For validation, 200 crash simulations with postures selected using a Sobol DOE, whose points differed from those of the training set, were run with two different restraint systems (see Fig. 2): 1) a restraint system that utilized the catalog controller (RSC), which applied a restraint law corresponding to the posture class, and 2) a restraint system that always applied the restraint law optimized for the standard posture (RSN).

While the RSC showed an average injury cost reduction of 21% compared with the RSN, the basic assumption was that the best restraint law from the catalog for a certain posture was the restraint law optimized at the center of the subregion that includes that posture [21].

The main objective of this study is to investigate the performance sensitivity of the nine optimized restraint laws previously determined within the posture space. The second goal is to develop performance-based classifiers and compare their performances with the previously derived region-based classifiers [21].
III. Variability of Restraint Laws Performance in the Posture Space

The complexity of the human–restraint system interaction may lead to sensitivity in the restraint system performance when the occupant posture deviates from the posture used in the optimization process. To investigate the global performance of the restraint laws included in the catalog, a uniform grid of 196 points (14 × 14) was selected in the posture space defined by the angles of lumbar and sideways flexion. Crash simulations were run with the occupant in the precrash postures corresponding to these grid points for each of the nine catalog restraint laws and the nominal restraint law. The normalized injury cost was calculated for each of the crash simulations. Then, the response surfaces were developed based on the injury cost values at the grid points using regression techniques (see Fig. 3). Multiple regions with local minimums observed in the contour plots prove that the injury cost in the posture space is a nonconvex function (a function with many extreme points). This finding supports the use of heuristics algorithms (e.g., genetic algorithms [21], simulated annealing [23], and the simplex method [24]) in the optimization of the restraint laws. These algorithms cover the whole design space, avoiding erroneous identification of a local optimum that may occur if local optimization algorithms (e.g., gradient-based algorithms) are used.

The potential of a restraint system, which asserts the best law from the catalog, was evaluated by selecting the best restraint law for each grid point [see Fig. 4(a)]. Restraint laws 5, 6, and 9 appear to be the best laws for more than half of the posture space (69.4%), and the most sensitive restraint laws (i.e., 2, 4, and 8) occur only at a few points (8.2%). 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 laws over the entire posture space. A contour plot showing the lowest injury costs for each point is shown in Fig. 4(b). The average injury reduction if the best restraint law is chosen from the catalog in each grid point is 29.7%.

IV. Performance of Restraint Systems With Catalog With a Reduced Catalog

The development of an RSC with less restraint laws may simplify the development of accurate classifiers and may result in a reduced production cost. Therefore, a balance must be found between minimizing the number of restraint laws $N_{RL}$ and maximizing the injury reduction across the entire posture region. The best restraint law combination for each $N_{RL}$ number of restraint laws (from 1 to 9) was determined by considering all $511 \left(\sum_{N_{RL}=1}^{9} N_{RL}! / (9 - N_{RL})!\right)$ possible combinations. The corresponding simulations were evaluated using the 196-posture set previously described by calculating the overall average injury reduction and comparing the results to the RSN. The best restraint law combinations were recorded, and their percentage breakdown was reported (see Table I).

It is shown 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 in injury increases as the number of restraint laws increases but

![Image of contour plots](image-url)
experiences diminishing returns (98% of the injury reduction obtained by nine RLs can be realized by using only five RLs). As shown in Table I, the last four RLs added to the catalog only account for approximately 13% of the posture space. In reality, the outcome of a collision for every restraint law cannot be known. Thus, statistical classifiers must be developed to choose the best restraint law given the sensor data available.

### TABLE I

<table>
<thead>
<tr>
<th>Nr.</th>
<th>Percentage (%) each RL produces minimum injury cost</th>
<th>Ovr. Inj. Red. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>100</td>
<td>20.9</td>
</tr>
<tr>
<td>2</td>
<td>39</td>
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<td>5</td>
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<td>29.7</td>
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<tr>
<td>4</td>
<td>23</td>
<td>29.7</td>
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</table>

V. DEVELOPMENT OF PERFORMANCE-BASED BAYES CLASSIFIERS

In our previous study [21], the set of classes \( \Omega \) was predefined as subregions of the posture space [see Fig. 1(b)] with restraint laws optimized for a posture in the middle of each subregion. In the current study, the training postures were grouped together, by which restraint law produced the lowest injury cost [see Fig. 4(a)]. Those postures were then used to estimate the distributions of the restraint law classes input into statistical classifiers, as described below.

Bayes classification is developed within a probabilistic framework and classifies objects using Bayes’ decision theory [25]. The decision principle behind Bayes’ decision theory is to assert the class \( \omega_j \) (from the set of classes \( \Omega = \{ \omega_1, \ldots, \omega_K \} \)), where \( K \) is the number of classes) that minimizes the overall risk with respect to the measurement vector \( \mathbf{x} \). The measurement vector \( \mathbf{x} \) describes the significant features of an object that will differ from class to class but also vary within the same class. In this paper, the measurement vector consists of the \( x-y \) coordinates of the occupant’s head measured by a stereo-vision camera (see Fig. 1).

A simplified version of the general Bayes classifier that assumes a unit cost function was employed in this study, which assumes a zero cost when an object is correctly classified and a cost of one when misclassified. This Bayes classifier, which is also known as the minimum-error-rate classifier, is defined as

\[
\phi_{\text{Bayes}}(\mathbf{x}) = \arg \min_j [p(\mathbf{x}|\omega_j)P(\omega_j)]
\]

where the conditional probability density function (pdf) \( p(\mathbf{x}|\omega_i) \) describes the probability distribution of the feature vector \( \mathbf{x} \) of a particular class, and the prior probability \( P(\omega_i) \) is based on previous knowledge about the classes independent of the feature vector.

The main challenge in developing Bayes classifiers is typically determining the conditional pdfs \( p(\mathbf{x}|\omega_i) \). The unknown conditional pdfs can be approximated using supervised parametric learning (SPL) and supervised nonparametric learning (SNL) methods. 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. While short descriptions of the statistical classifiers employed in this study are briefly outlined below, the reader is referred to van der Heijden et al. [25] or Duin et al. [26] for a more detailed treatment of pattern recognition algorithms.

A. SPL Classifiers

The SPL classification methods used in this study were linear discriminant classifier (LDC) and quadratic discriminant classifier (QDC). QDC assumes that the measurement vectors coming from an object of class \( \omega_k \) are normally distributed with mean vector \( \mu_k \) and covariance matrix \( C_k \). In the 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., \( C_k = \text{constant} \)). In the LDC case, the decision boundaries in the two-feature case are linear [25].

B. SNL Classifiers

SNL classifiers are much more general than SPL classifiers, but they require larger training sets to obtain an accurate classification. The SNL classifiers used in this study were support vector machine (SVM), Parzen (PARZ), and nearest neighbor (NN) classifiers.

1) SVM Classifiers: SVM is a nonlinear classifier that forms decision boundaries by maximizing the margin between 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 \( \mathbf{x}_n, n = 1, \ldots, N \) (where \( N \) is the number of samples) [25], [26]. Maximizing the separation boundary is equivalent to minimizing \( \|\mathbf{w}\|^2 \), which is usually solved using standard software packages. In the case of nonseparable data, a regularization parameter \( R \) defines the balance between limiting misclassified objects and maximizing the overall margin (i.e., \( \|\mathbf{w}\|^2/2 + R(\Sigma_n \xi_n) \) instead of \( \|\mathbf{w}\|^2 \) as in the separable case).

The regularization parameter \( R \) is crucial in determining the class boundaries when there are overlapping classes since it can account for outliers that would greatly change which support vectors are selected. To find an appropriate value for \( R \), the cross-validation method was utilized [25] to base the decision on an estimated error rate of the classifier. 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 included 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 to find an estimated error rate. A special case of the cross-validation method divides the training set into
the smallest subset 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 [25].

To increase generality of the SVM classifier, its boundaries are changed from the linear form to a nonlinear form using a method known as the “kernel trick.” In this case, the inner product between the measurement vectors \((x_m, x_n)\) [25] is replaced by a more general kernel function \(K(x_m, x_n)\). In this paper, two kernel functions were selected: a radial basis function [referred to as SVM\(_p\) (2)] and a polynomial function [referred to as SVM\(_p\) (3)]. Thus

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

\[
K(x_m, x_n) = (x_m^T x_n + 1)^p \tag{3}
\]

The width of the radial basis function \(\sigma\) and the degree of the polynomial function \(p\) were optimized using the cross-validation method as well. To optimize the kernel parameters and the regularization parameter simultaneously, a range was selected for the kernel parameters and individually considered. 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 [25].

2) PARZ Classifiers: The algorithm for the PARZ classifier is obtained by replacing the conditional pdf with the PARZ estimation \(\hat{p}(x|\omega_k)\) in the general Bayes classifier [see (1)], i.e.,

\[
\phi_{\text{PARZ}}(x) = \arg\min_j \left[ \hat{p}(x|\omega_j) \hat{P}(\omega_j) \right]. \tag{4}
\]

The PARZ estimation approximates the conditional pdfs \(\hat{p}(x|\omega_k)\) by separately considering each of the training subsets \(T_k\) for each class \(\omega_k\) [25]. The probability is assumed to have a maximum at the point in the measurement space where the training measurement vector \(x_j\) is located. Then, the probability is assumed to decrease as the distance \(\rho(x, x_j)\) increases from \(x_j\) as less is known about the class of the measurement vector. This is done for all measurement vectors \(N_Kx\) in a given class \(\omega_k\). The kernel functions for all of the measurement vectors are then summed and normalized to attain an estimate for the conditional density. Thus

\[
\hat{p}(x|\omega_k) = \frac{1}{N_k} \sum_{x_j \in T_k} h(\rho(x, x_j)) \tag{5}
\]

where a kernel function \(h(\rho(x, x_j))\) has a maximum at \(x = x_j\), monotonically decreases as \(\rho(x, x_j)\) increases, and is normalized over the entire space.

3) NN Classifiers: NN classification uses a special technique that classifies objects without explicitly estimating probability densities. The identification of an object using this method considers a hypersphere with dimension equal to the length of the measurement vector where the center is the test sample in question. The volume of this hypersphere is denoted by \(V(x)\). 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

\[
\hat{p}(x|\omega_j) = \frac{K_j}{N_j V(x)} \tag{6}
\]

where \(K_j\) is the number of samples out of the \(K\)-NNs for \(\omega_j\). The prior probability for each class can be estimated using

\[
\hat{P}(\omega_j) = \frac{N_j}{N_K}. \tag{7}
\]

Using the Bayes framework, the asserted class can be found by substituting (6) and (7) into (1). Simplifying the equation by eliminating the terms that do not depend on \(j\) results in

\[
\phi_{\text{KNN}}(x) = \arg\min_j [\hat{p}(x|\omega_j) P(\omega_j)] = \arg\min_j [K_j]. \tag{8}
\]

Thus, the decision algorithm simplifies to asserting the class that has the most samples out of the \(K\)-NNs considered [25]. For this study, \(K\) was optimized for each optimum catalog combination using the leave-one-out method [26]. Table II lists the optimized values for \(\sigma, p\) (for SVM classifiers), and \(K\) (for \(K\)-NN classifiers).

VI. Verification of Performance-Based Bayes Classifiers

The performance of the restraint systems with catalog controllers (RSCs) and statistical classifiers was evaluated using two validation sets. The first 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. The second validation set is the set used in our previous study [21] that consisted of 200 Sobol postures varying lumbar flexion, sideways flexion, neck flexion, and seating position. The two additional posture parameters varied in this set can be interpreted as “signal noise” to see how well the classifiers adapt to variations in posture not included in the posture recognition training process.

An example of the class boundaries for the different classifiers for the three-class case is presented (see 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 that result in concave nonlinear boundaries and divide the posture class into distinct convex classes. Complex boundaries that result in concave nonlinear boundaries and divide the posture class into distinct convex classes.
The majority of misclassified points occur along the boundaries of classifiers in both the training and validation sets, but there are also misclassified samples all over the regions. It is important to note that a misclassified posture does not necessarily imply poor performance. The second or third best restraint law could potentially only perform slightly worse than the “best” classifier for a particular posture. The percentages of correct classified postures by each classifier in both training sets are reported in Table III.

Crash simulations were performed with the occupant in all postures from both validation sets (1 and 2) 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 that can be obtained for the precrash posture $\omega_i$, i.e.,

$$\text{IR}_{\text{opt},\omega_i} = \max_{k=1,10} \left( \frac{\text{inj}_{\text{RSN},\omega_i} - \text{inj}_{k,\omega_i}}{\text{inj}_{\text{RSN},\omega_i}} \times 100 \right)$$

Table III

<table>
<thead>
<tr>
<th>Nr.</th>
<th>RL</th>
<th>LDC (%)</th>
<th>QDC (%)</th>
<th>SVMp (%)</th>
<th>SVMr (%)</th>
<th>PARZ (%)</th>
<th>K-NN (%)</th>
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<tbody>
<tr>
<td>2</td>
<td>74/70</td>
<td>76/72</td>
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<td>55/43</td>
<td>52/41</td>
<td>61/43</td>
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</table>

where $\text{inj}_{k,\omega_i}$ and $\text{inj}_{\text{RSN},\omega_i}$ are the injury costs recorded with restraint law $k$ and nominal restraint, respectively.

The average injury reduction of an optimal system ($\text{IR}_{\text{opt}}$) and an RSC system with a posture classifier $J$ ($\text{IR}_J$) was
calculated as the average injury reduction for all postures \( N (N = 200) \) included in the validation set \( k \), i.e.,

\[
IR_{\text{opt}} = \frac{\sum_{i=1}^{N} \text{inj}_{\text{opt}, i}}{N}, \quad IR_J = \frac{\sum_{i=1}^{N} \text{inj}_{J, i}}{N}.
\] (10)

As expected, the optimal average injury reduction increases as the number of restraint laws increases (see Fig. 6). In addition, a lower percentage of injury cost reduction was obtained in validation set 2 than in validation set 1 due to the variations of the seat position and neck flexion. The values of the maximum average injury reduction (30.4% and 29.1% in set 1 and set 2, respectively) in the validation sets were close to the corresponding value obtained in the training set (29.7%).

The performance of the posture classifiers varies with respect to the number of restraint laws and the validation set. For validation set 1 [see Fig. 6(a)], the QNC and SVM\(_p\) showed the highest performance for a reduced number of restraint laws (up to five). However, as the number of restraint laws increases, the performance of these classifiers decreases. The performance of PARZ and \(K\)-NN classifiers showed a monotonically increasing behavior with respect to the number of restraint laws. These classifiers performed best out of all the classifiers investigated for more than five restraint laws.

As in the case of validation set 1, the performance of the SVM classifiers for validation set 2 initially increases with respect to the number of restraint laws but then decreases for more complex catalogs [see Fig. 6(b)]. SVM\(_p\) was the best classifier for the catalogs with two and three restraint laws. For the catalogs with restraint laws greater than three, the highest performance was achieved by the PARZ, \(K\)-NN, and QNC classifiers, which achieved 82%–84% of the optimal performance [see Fig. 6(b)].

Computational time was defined as the amount of time needed to receive the sensor signals related to posture, process the signals to identify the posture of the occupant, and select the appropriate restraint law given the situation. As shown in Table IV, the SPL classifiers (LNC and QNC) and \(K\)-NN classifiers require the lowest amount of computational time during the validation process (under 0.02 ms and about 0.04 ms, respectively). Both SVM classifiers showed to be the most computational expensive, but overall, their computational time was under 0.72 ms, showing that this type of methodology can be applied in real-time applications.

### VII. DISCUSSION

Vehicle 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 nontrivial 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” precrash posture (relaxed posture) involved in a “typical” collision (e.g., frontal collision with a 56-km/h initial velocity [28]). In the current study, the performance of a restraint system obtained by this fixed optimization approach showed a significant sensitivity when the occupant precrash posture was varied (see Fig. 3). A crash simulation study with volunteers [29] reported that only 17% of passengers were close to nominal posture during the precrash phase; therefore, these results may highlight the need for adaptive restraint systems that take into account occupant and vehicle characteristics [see Fig. 4(b)]. While the lack of a musculature system in ATDs and the high cost of crash tests may make implementation of a testing approach in regulation difficult, integration of numerical crash simulations in a standardized automotive R&D process may be a promising tool for designing safer vehicles [30]–[32].

A paradigm that permits most of the computational work to be done “offline” was developed, generating a database that can be efficiently mined in real-time during a crash event to obtain near-optimal control law selection for the restraint system. To reduce the complexity of the problem, it was assumed that all collision variables were known and fixed, whereas the occupant precrash posture and restraint parameters were varied and unknown.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>RL 2</th>
<th>RL 3</th>
<th>RL 4</th>
<th>RL 5</th>
<th>RL 6</th>
<th>RL 7</th>
<th>RL 8</th>
<th>RL 9</th>
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<tr>
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<td>370</td>
<td>426</td>
<td>491</td>
<td>676</td>
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<td>230</td>
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\* – the computational time recorded on an Intel Core2Quad 2.4 GHz processor Q6600, 8 GB DDR2 RAM
A Bayesian approach was applied to select an appropriate restraint law for a certain occupant posture [21]. A usual approach in the safety field is to divide the occupant space into regions for the occupant classification process [21]. A parametric study to investigate the global performance of the nine restraint laws (determined in a previous study [21]) was performed using a uniform grid of 196 postures varying lumbar and sideways flexion. The results showed that assuming that a restraint law optimized for a particular posture will be the best option locally is usually false. In addition, these restraint laws showed various overall performances over the whole space. While restraint laws 5 (the center of the posture space) and 6 had the most uniform performance in the posture space, restraint laws 4 and 2 (the class that contains the standard posture) were the most sensitive to changes in posture. These results suggest that the performance of our previous restraint system (up to 21% injury reduction with respect to the nominal system) could be improved if a better definition of classes was found.

Testing all nine restraint laws for the postures corresponding to a 196 uniform grid into lumbar flexion–sideways flexion posture space showed that an average injury reduction of 30% relative to the nominal restraint system can be obtained if the restraint laws are defined based on performance. Therefore, the possibility of using a reduced number of restraint laws was investigated. The average injury reduction for the best restraint law combinations showed significant improvement from \( N_{RL} = 1–6 \), then remained fairly constant from \( N_{RL} = 6–9 \). The optimal number of restraint laws tended to be 5–7, when about 96%–99% of the maximum injury reduction relative to the nominal restraint system can be achieved in both validation sets. This may have been due to the fact that the last two restraint laws poorly performed over the entire region (RLs 2 and 4). The highest relative performance was obtained in validation set 1 (30.4% for \( N_{RL} = 9 \)) for the 200 postures that maintained the seating position and neck flexion angle fixed similar to the training set. Varying the seating position and neck flexion angle in validation set 2 decreased the optimal reduction by 1.3%–2.2% with respect to validation set 1. This relatively low reduction in performance proves that seating position and neck flexion have relatively low influence on overall injury cost, as was concluded in our previous study [21].

While all performance-based classifiers showed higher performance (even for lower numbers of restraint laws) than the region-based classifiers developed in previous study, several types of classifiers stood out among the rest. In the case of validation set 1, which had a similar structure as the training set (only lumbar and sideways flexion were varied), the two SNL classifiers (K-NN and PARZ) showed the highest performance. In addition to these SNL classifiers, QNC classifiers performed very well when the neck flexion and seating position were varied in validation set 2. SVM classifiers also showed good performance but only for lower numbers of restraint laws (up to 5–6). The computational time for all classifiers was under 0.7 \( \mu S \) (in the case of SNL classifiers, it was under 0.02 \( \mu S \)). This occupant classification method is a computationally efficient process appropriate for automotive crashes (\( \sim 100 \mu S \)).

The restraint law catalogs developed in this study were limited by the nine restraint laws developed in a previous study [21]. The performance of RSCs can be improved by adding more possible restraint laws and optimizing more restraint parameters (e.g., pretensioner stroke). However, a challenging question would be choosing the best approach to attain these restraint laws: point optimization, region optimization, simply choosing some parametric restraint laws in the restraint space (without optimization), or another approach. It is believed that more research in this field is needed to determine the optimum approach. In addition, higher injury reduction percentages are expected by varying other occupant characteristics in the classification process (e.g., age, sex, and anthropometric data) and testing nonstandard collisions (i.e., offset pole crash instead of a standard frontal collision).

VIII. CONCLUSION

This study numerically investigated the development of an adaptive restraint system [33], [34] that selects from a catalog the most appropriate restraint law corresponding to an occupant’s precrash posture. A catalog of restraint laws optimized in a previous study [21] for nine postures that were uniformly distributed in posture space was employed. The performance of these restraint laws locally optimized showed significant sensitivity when they were evaluated over the entire posture space. 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 reducing occupant injury cost during a crash. The RSC with performance-based classifiers showed an injury reduction as high as 28.2% compared with region-based classifiers, which attained an injury reduction of up to 21%. Improved performance is expected in future studies by expanding the number of restraint laws tested, experimenting with different restraint parameters, and exploring different sensor signals (features) that more clearly define restraint law boundaries, thus improving classifier accuracy and effectiveness.

APPENDIX

A genetic algorithm was used to optimize the restraint laws [21] for the nominal posture and the centroid of each posture class (see Fig. 1).

The following parameters were chosen as design variables for the restraint laws (see Table V): the retractor pretensioner...
firing time \( t_{\text{ret}} \), lap belt pretensioners firing time \( t_{\text{lapse}} \), airbag firing time \( t_{\text{airbag}} \), airbag mass flow rate \( m_{\text{fr,airbag}} \), and load-limiting belt force \( L_{\text{belt}} \). The lap belt pretensioners refer to pretensioners located at both anchoring points of the lap belt. The mass flow rate for the airbag inflator was defined to deliver a peak airbag volume of 60 l at approximately 35 ms after the airbag firing time. For this optimization routine, the function for mass flow rate was multiplied by the scalar quantity \( m_{\text{fr,airbag}} \).

REFERENCES


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