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Reference Governors for Controlled Belt Restraint Systems

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Abstract— **This paper presents a novel control strategy for real-time controlled restraint systems. Today's restraint systems typically include a number of airbags, and a three-point seat belt with load limiter and pretensioner. In the class of real-time controlled restraint systems, the restraint actuator settings are continuously manipulated during the crash. The control strategy developed here is based on reference management, in which a nonlinear device - a reference governor - is added to a primal closed loop controlled system. This governor determines an optimal setpoint in terms of injury reduction and constraint satisfaction by solving a constrained optimization problem. Prediction of the vehicle motion, required to predict future constraint violation, is included in the design and is based on linear regression of past crash data. Simulation results with a MADYMO model show that a significant injury reduction is possible, without prior knowledge of the crash. Furthermore, it is shown that the algorithms are sufficiently fast to be implemented on-line.**

I. Introduction

Today's restraint systems typically include a number of airbags, and a three-point seat belt with load limiter and pretensioner. The design and testing of these passive safety devices is primarily oriented towards the male 50^{th} percentile Hybrid III dummy (50%ile HIII) for a set of standardized, high speed crashes, and additional testing is performed with 5%ile female and 95%ile male dummy [1].

This design already indicates the limitation of current restraint systems. In the first place, the restraint design has to be effective for a whole range of occupants without the possibility to optimize for the actual situation. Indeed, the restraint system is generally not able to adjust its characteristics to the occupant type. Hence, the design is a tradeoff between the various dummy types. Secondly, the restraint configuration is geared towards the situation where it gives as much protection as possible in the standardized crash test. Although these tests are severe, restraints will usually not be optimal under all different conditions. These two fundamental shortcomings of current restraint systems makes that a vehicle occupant will not be optimally protected in every crash condition.

A. Controlled Restraint Systems

Occupant safety is significantly improved by *adaptive* restraint systems. These restraint systems adjust their configuration during the crash according to the current operating environment, such as the occupant size and position, and crash conditions. In literature, adaptive restraint systems are also dubbed *smart* restraint systems [2], [3], *intelligent* restraint systems [4], [5], *active* restraint systems [6], [7], [8] or *advanced* restraint systems [9].

A very important part of any adaptive system is the use of sensors to identify the current operating environment. Since an increasing number of sensors are being integrated in today's vehicles, the use of more advanced adaptive restraint systems has become possible in present state-of-the-art vehicles [10]. Examples are load limiters with multiple levels and dual- or multistage airbags [11], [12], [13].

Restraint systems could deliver a near optimal protection when they are manipulated as a function of measured signals during the full duration of the crash. In that case, the system is referred to as a *continuously controlled* restraint system. The continuous manipulation can be performed through a control algorithm that aims at minimizing one or more injury criteria (IC). IC's are defined as indices of one or more biomechanical responses of the occupant, such as head acceleration, chest compression, etc. [14]. The control algorithm provides the control values to an actuator based on measured or estimated biomechanical responses. The actuator then continuously alters the restraint system element, e.g. load limiter force, airbag vent size or belt position. A schematic representation of the components of a controlled restraint system is shown in Fig. 1.

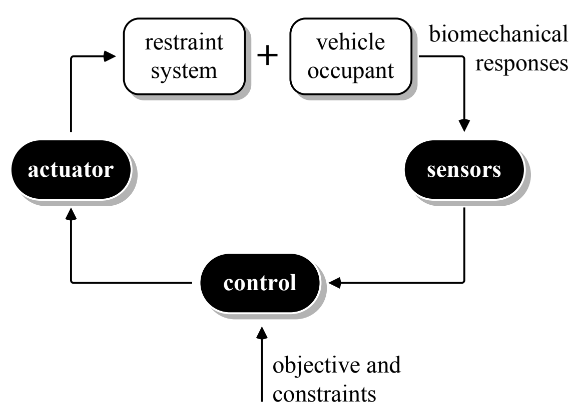

Fig. 1. Schematic representation of a Continuously Controlled Restraint System

Although this class of restraint systems are not yet available in today's passenger vehicles, numerical simulations with a controlled seat-belt and/or airbag showed that a significant injury reduction can indeed be achieved [8], [15], [7], [16]. Therefore, this class of systems will be a main focus of future restraint system development, and this paper contributes to this development.

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B. Problem definition

One of the major issues in controlled restraint systems concerns the design of the control algorithm to determine the restraint actuator input. To obtain minimal injury criteria values in every scenario, the biomechanical responses have to follow an optimal trajectory. This trajectory is heavily dependent on the vehicle deceleration pulse during the crash, the occupant type and constraints like the available space in the vehicle's interior. Since the crash pulse is not known in advance, the vehicle motion has to be predicted in order to determine these optimal trajectories. The problem at hand is thus to develop a control algorithm that - based on the available measurements from the sensors - computes the optimal control signals for the actuator. Moreover, the algorithm must be computationally feasible so that it meet the requirements real-time.

C. Contribution

The main contributions of this paper are as follows: (i) a control strategy is proposed that is able to determine optimal restraint settings without pre-crash information, aiming at a minimum risk of injury for the occupant, (ii) algorithms are developed, based on constrained optimization problems, that implement the proposed control strategy and are able to run in real-time, (iii) simulation results with an actuated belt and a MADYMO occupant model show that a significant injury reduction can be achieved for the thoracic region without pre-crash information, (iv) it is shown that the proposed control strategy is generic and can be extended to multiple injury criteria.

The paper is organized as follows. Section II describes the approach to handle the constrained control and predictive problems at hand. The method consists of a setpoint optimization and crash pulse prediction algorithm, and they are explained in section III and IV, respectively. Finally, section V shows the simulation results and the last section outlines the conclusions and future work.

II. Control Strategy

A. Reference management

Reference management [17] is a predictive control method that acts on the setpoint or reference signal, rather than the control signal, and can be considered as a subclass of Model Predictive Control (MPC) [18]. The main idea of reference management is to add a nonlinear device, called a Reference Governor (RG), to a primal compensated control system, see Fig. 2. This latter system is designed to be stable and has good tracking performance in the absence of constraints. Whenever necessary, the RG modifies the setpoint provided to the primal control system to avoid future constraint violation. Since the RG does not influence the closed-loop behavior of the system, stability remains guaranteed by this approach. These feature makes RG of interest within the context of controlled restraint systems.

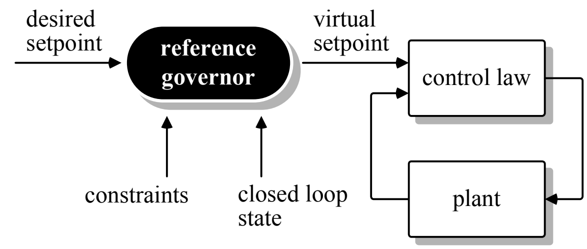

Fig. 2. Reference management

B. Primal compensated control system

In this paper, the primal compensated system is based on control of the absolute chest acceleration, a_{chest}, of the occupant. The control setup is graphically depicted in the lower part of Fig 3. A desired setpoint, r, for the chest acceleration is defined, and tracking is achieved by control of a belt force actuator, F_{belt}, which replaces the conventional load limiter. The desired setpoint r has to be computed such that it minimizes the peak value of a_{chest}, which is associated with the 3ms clip injury criterion A_{max} [14]. Additionally, constraints have to be satisfied on the chest displacement, x_{rel}, and chest velocity relative to the vehicle interior, v_{rel}. These constraints prevent the occupant from hitting the steering wheel - which would cause even more severe injuries. The crash pulse or vehicle acceleration a_{veh} acts as a disturbance on the system. Initial simulation results with such a controlled restraint system can be found in [7], [16].

Remark 2.1: Although the injury criterion A_{max} is an important injury risk predictor [14], thoracic injury measures like chest deflection, D_{max} or VC are at least equally important [19]. The advantage of the A_{max} criterion is that the constraints can be included in the setpoint without using an occupant model. However, it is of interest to extend the current approach to include D_{max} or VC.

C. Reference governor design

The reference management control strategy is appealing, because of the separation of stability and performance, as mentioned before. In literature however, applications are limited to systems with constant reference signals or small disturbances. Since variations on the disturbance a_{veh} are significantly, and the optimal setpoint is not a constant, it is necessary to adapt the currently available methods. Instead of modifying a predefined reference signal, the setpoint is found by solving an optimization problem on-line. The algorithm is divided into two actions, see Fig. 3:

1) Setpoint optimization: Based on the current state of the closed loop system, x_{cl}, and a prediction of the vehicle motion, a setpoint r is constructed that minimizes A_{max} and satisfies the constraints. The setpoint will be updated at a frequency $f_o = 1/T_o$, with T_o the optimization period.
2) Crash prediction: An algorithm to predict future vehicle motion is included in the RG design. It is assumed

that the acceleration signal of the vehicle a_{veh} can be measured during the crash, and it is proposed to use the entire motion history to predict future behavior. The crash prediction is updated at a frequency $f_p = {}^{1}/_{T_p}$, with T_p the prediction period.

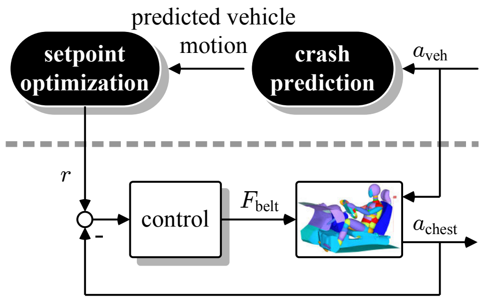

Fig. 3. Reference governor design (top) for the controlled belt restraint system (bottom)

III. Setpoint Optimization

It is shown here that the constrained optimization problem as defined previously can be written as a linear program (LP), which can be solved efficiently [20].

A. Optimization problem

Firstly, it is mentioned that the signals will be sampled with sample time T, and typically $T \ll T_p$ and $T \ll T_p$. The current time t_c is now $t_c = kT$ with $k = 0, 1, 2, \dots, N$, where N follows from the (assumed) duration of the crash t_e, so $N = {}^{(t_e - t_c)}/_{T}$. In the optimization problem, constraints have to be satisfied on the relative chest displacement and velocity. This relative motion is simply given by

$$\begin{aligned} x_{\text{rel}}(k) &= x_{\text{chest}}(k) - x_{\text{veh}}(k) \\ v_{\text{rel}}(k) &= v_{\text{chest}}(k) - v_{\text{veh}}(k) \end{aligned} \tag{1}$$

with x_{veh} and v_{veh} the absolute vehicle displacement and velocity, respectively. The absolute chest motion at the next sample is predicted by

$$\begin{aligned} x_{\text{chest}}(k+1|k) &= x_{\text{chest}}(k) + T v_{\text{chest}}(k) \\ v_{\text{chest}}(k+1|k) &= v_{\text{chest}}(k) + T a_{\text{chest}}(k) \end{aligned} \tag{2}$$

The notation $x_{\text{chest}}(k + j|k)$ is common to denote the prediction of signal $x_{\text{chest}}(k+j)$ with knowledge up to time k.

Ideally, the chest acceleration a_{chest} tracks the setpoint trajectory r. Provided that the primal closed loop is sufficiently fast, the acceleration prediction is defined by

$$a_{\text{chest}}(k+j|k) := r(k+j) \qquad \forall\ j = 1, \dots, N \tag{3}$$

with $r(k+j)$ the setpoint trajectory implemented at time k. With the above definition, it is shown that the predictions of the relative chest displacement and velocity, $x_{\text{rel}}(k+j|k)$ and $v_{\text{rel}}(k+j|k)$, depend on the setpoint trajectory $r(k+j)$.

The setpoint optimization problem introduced in Section II-B can now be written as

$$\begin{aligned} \min \quad & \max_{j \in \{1,\dots,N\}} |r(k+j)| \\ \text{s.t.} \quad & l_1 \le x_{\text{rel}}(k+j|k) \le l_2 \\ & v_{\text{rel}}(k+N|k) \le 0 \end{aligned} \tag{4}$$

So the displacement relative to the vehicle interior, x_{rel}, is constrained by l_1 and l_2, and the relative velocity v_{rel} at the end of the crash has to be smaller or equal to zero.

B. Linear programming

The min-max problem in (4) can be rewritten as a linear program (LP) by introducing an auxiliary variable γ. This γ represent the maximum of the absolute value of $r(k+j)$. Then

$$\min \quad \max_{j \in \{1,\dots,N\}} |r(k+j)|$$

is equivalent to

$$\begin{aligned} \min \quad & \gamma \\ \text{s.t.} \quad & -\gamma \le r(k+j) \\ & r(k+j) \le \gamma, \quad j = 1, \dots, N \end{aligned} \tag{5}$$

The constraint equations also depend linearly on the design variables. To show this, equations (1)-(3) are used, and the relative chest displacement and velocity at time k can be written as

$$\begin{aligned} x_{\text{rel}}(k+j|k) &= x_{\text{chest}}(k) + jT v_{\text{chest}}(k) - \dots \\ & \quad\ x_{\text{veh}}(k+j|k) + \dots \\ & \quad\ T^2 \textstyle\sum_{i=1}^{j-1} (j-i) r(k+i) \\ v_{\text{rel}}(k+j|k) &= v_{\text{chest}}(k) - \dots \\ & \quad\ v_{\text{veh}}(k+j|k) + \dots \\ & \quad\ T \textstyle\sum_{i=0}^{j-1} r(k+i) \end{aligned} \tag{6}$$

The design variables are stacked in a vector $x \in \mathbb{R}^{N+1}$ as follows

$$x = \begin{bmatrix} r(k+1) & r(k+2) & \dots & r(k+N) & \gamma \end{bmatrix}^T \tag{7}$$

Then equations (5) and (6) can be written in the standard form of an LP

$$\begin{aligned} \min_{x} \quad & f^T x \\ \text{s.t.} \quad & Ax \le b \end{aligned} \tag{8}$$

with $f \in \mathbb{R}^{N+1}$ and $f = \begin{bmatrix} 0 & \dots & 0 & 1 \end{bmatrix}^T$.

The constraint equation matrix A is a constant which depends on the sample time T only.

Remark 3.1: When it is desirable to include other constraints, e.g. the maximum belt force, in the optimization problem, the matrix A will also contain a (linear) model of the primal compensated system.

The vector b is a linear function of only measurable variables, the future vehicle displacement and constants. So

$$b = g(a_{\text{chest}}(k), x_{\text{veh}}(k+j|k), l_1, l_2, T) \tag{9}$$

with g a linear function.

The problem in (8) can now be efficiently and accurately solved by simplex or interior point methods [20].

C. Results

The algorithm is implemented in Matlab, and results are generated for $l_1 = -0.03$ m, $l_2 = 0.2$ m, $f_o = 100$ Hz, $t_e = 0.2$ s, $T = 0.1$ ms and with full a priori crash information of x_{veh} and v_{veh}. So the crash prediction step in Fig 3 is not used here. Fig. 4 shows the crash pulse, and the optimal setpoint r, which is indeed near constant, without violating constraints. Each optimal solution was found within a few milliseconds on an average workstation[1], which is smaller than the optimization period $T_0 = 10$ ms.

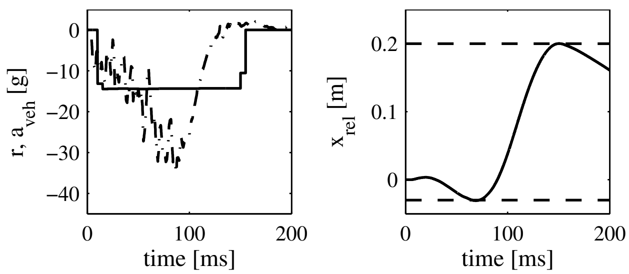

Fig. 4. Left: The optimal setpoint (solid) for the chest acceleration given a vehicle acceleration (dash-dotted). Right: The relative chest displacement does not violate the constraints

IV. Prediction of Vehicle Motion

A. Objective function

In the previous section, an algorithm is presented that generates a chest acceleration setpoint r, based on a priori knowledge of the vehicle motion. Knowledge of future vehicle motion is obviously not available during the crash, and a prediction of this motion is required. From equation (9), it becomes clear that not the crash pulse a_{veh}, but the vehicle displacement x_{veh} should be accurately known. This is an important observation, as the displacement is a far smoother signal than the acceleration and can therefore be better approximated. This has led to the idea to fit a vehicle displacement function, $\hat{x}_{\text{veh}}(t)$, to the available measurement data by regression analysis. To obtain a reasonable prediction in absence of a sufficient amount of data, it is assumed that the vehicle reaches zero velocity at 0.15 s after impact, so $\hat{v}_{\text{veh}}(t) = 0$ for $0.15 \le t \le t_e$.

The objective function to be minimized is the sum of the squared residuals:

$$\int_0^{t_c} |\hat{x}_{\text{veh}}(t) - x_{\text{veh}}(t)|^2 dt + \int_{0.15}^{t_e} |\hat{v}_{\text{veh}}(t)|^2 dt \qquad (10)$$

with t_c the current time.

To write this problem in a convenient format, three assumptions are made

1) the velocity at the start of the crash, $\hat{v}_{\text{veh}}(0) = v_o$, is exactly known
2) the initial position and acceleration are zero, i.e. $\hat{x}_{\text{veh}}(0) = \hat{a}_{\text{veh}}(0) = 0$
3) the vehicle acceleration is measured during the crash with sample time T, and its velocity and position are known instantaneously

[1]contains a CPU that runs at 1.4 GHz

B. Linear regression

We will approximate the displacement path of the vehicle by a polynomial of order n:

$$\hat{x}_{\text{veh}}(t) = p_0 + p_1 t + p_2 t^2 + p_3 t^3 + \cdots + p_n t^n$$

It follows from initial conditions that $p_0 = p_2 = 0$ and $p_1 = v_o$. The remaining parameters are stacked in a parameter vector p

$$p = \begin{bmatrix} p_3 & p_4 & \dots & p_n \end{bmatrix}^T$$

The vehicle motion approximations can be written linearly in p, as follows

$$\hat{x}_{\text{veh}}(t) = A_x(t)p + v_o t \qquad (11)$$

$$\hat{v}_{\text{veh}}(t) = A_v(t)p + v_o \qquad (12)$$

with functions

$$A_x(t) = \begin{bmatrix} t^3 & t^4 & \dots & t^n \end{bmatrix} \qquad (13)$$

$$A_v(t) = \begin{bmatrix} 3t^2 & 4t^3 & \dots & nt^{n-1} \end{bmatrix} \qquad (14)$$

As mentioned above, the vehicle motion measurement is sampled at the time instances $t \in \{0, T, 2T, \dots, t_c\}$. We assume that the vehicle velocity reaches zero velocity at the time instances $t \in \{0.15, 0.16, \dots, t_e\}$ s. Now the functions $A_x : \mathbb{R} \to \mathbb{R}^{n-2}$ and $A_v : \mathbb{R} \to \mathbb{R}^{n-2}$ are used to create the two following matrices

$$A_p = \begin{bmatrix} A_x(0) \\ A_x(T) \\ \vdots \\ A_x(t_c) \\ A_v(0.15) \\ A_v(0.16) \\ \vdots \\ A_v(t_e) \end{bmatrix}, \quad B_p = \begin{bmatrix} x_{veh}(0) \\ x_{veh}(T) - v_o T \\ \vdots \\ x_{veh}(t_c) - v_o t_c \\ -v_o \\ -v_o \\ \vdots \\ -v_o \end{bmatrix}$$

The matrices A_p and B_p are used to obtain a discretized version of the objective function (10), and the optimization problem can be written as

$$\min_p \|A_p p - b_p\|_2^2$$

The objective function is now linear in the parameters p. It is well-known, see e.g. [20], that the analytical solution to this linear regression problem is $p^* = (A_p^T A_p)^{-1} A_p^T b_p$, assuming A_p has full column rank. Suppose that $t_e = 0.15$ s, then $A_p \in R^{(t_c/T) \times (n-2)}$ and one can easily verify that A_p has full column rank for $t_c \ge (n-2)T$.

With the solution for p and (11), a prediction for $x_{\text{veh}}(t|t_c)$ can be made for $t > t_c$. This prediction can then be used in the setpoint optimization algorithm, see equations (9) and (8).

C. Results

The prediction algorithm described above is not likely to accurately predict the displacement of a large horizon, because of the uncertain nature of a crash event. Therefore, only the maximum absolute error over a relatively small prediction horizon of 50 ms is used to evaluate the accuracy, referred to as e_{50}. A constraint violation might occur after this 50 ms horizon, caused by an inaccurate vehicle prediction. However, since a more accurate vehicle prediction becomes available every $T_p < 50$ ms, and a new setpoint is computed every $T_0 < 50$ ms, it is likely that the erroneous setpoint is corrected within 50 ms. This is an additional argument that prediction errors within the 50 ms horizon are most relevant.

A large set of crash pulses from vehicles in frontal EuroNCAP and USNCAP impacts is exploited to test the accuracy of the algorithm. In Fig. 5, the e_{50} values for 18 different crashes are averaged for different approximation orders n and for $f_p = 100$ Hz. It shows that for $n = 7$ the best results are obtained, leading to e_{50} errors of less than 7 cm. Given that the relative displacement of the chest is in the order of 20-30 cm, this is an acceptable error value. So although the crashes differ substantially in magnitude, impact velocity and duration, the displacement is predicted with reasonable accuracy, when there is 30-50 ms of crash history data.

The information about the maximum prediction error at every time instant is implemented in the setpoint optimization problem by using a so-called robustness parameter, as will be shown next in the simulation setup.

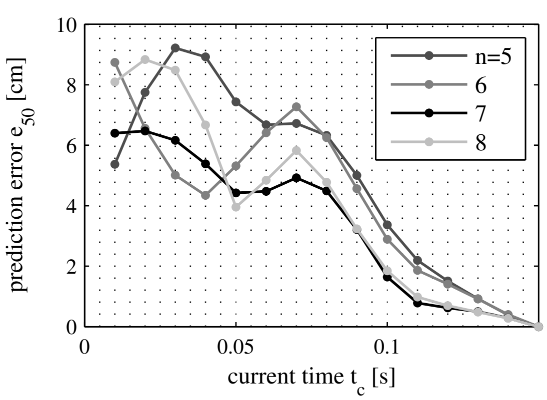

Fig. 5. Mean e_{50} values over 18 different crash pulses

V. Simulation Results

The objective of the RG is to generate a setpoint r for the chest acceleration using the receding horizon principle, such that the A_{max} injury criterion is minimized and constraints on the relative chest motion will not be violated. In this section, the results are shown of the setpoint optimization, combined with the vehicle prediction from the previous section. To accommodate for the prediction errors in vehicle displacement path, a robustified version of the setpoint optimization algorithm from section III is proposed first.

A. Robustness

The setpoint optimization algorithm is made robust against the vehicle prediction error, which is inevitable. Robustness is implemented by lowering the bounds in the constraint equations in (4) by $\epsilon(k)$, hence

$$\begin{aligned} l_1 + \epsilon(k) \quad &\le x_{\text{rel}}(k+j|k) \quad \le l_2 - \epsilon(k) \\ &\le v_{\text{rel}}(k+N|k) \quad \le 0 \end{aligned}$$

The robustness function $\epsilon(k)$ is a linearly decreasing function of current time $t_c = kT$, so the bounds become less conservative as the crash progresses, and the prediction of the vehicle displacement becomes more accurate. The function $\epsilon(k)$ is based on the prediction error results from the previous section, see Fig. 5.

B. Reference Governor with vehicle prediction

Results with the combined RG, i.e. the robust setpoint optimization and the vehicle prediction, are generated at update frequencies $f_o = f_p = 100$ Hz, and with a sample time of $T = 0.1$ ms. Fig. 6 shows the results of the RG for the same EuroNCAP frontal impact pulse as in Fig. 4. It illustrates that the calculated setpoint, based on a vehicle motion prediction, is desirably close the optimal setpoint, obtained with a priori crash information. This implies that without knowledge of the crash, almost optimal behavior can be predicted in terms of the injury parameter $A_{\max}$ for the considered impact pulse. Note there is a slight constraint violation on the upper bound, due to errors in the vehicle prediction.

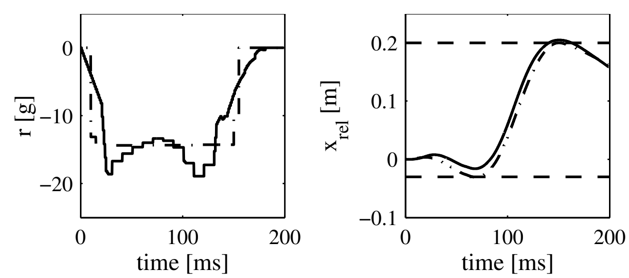

Fig. 6. Left: The optimal setpoint for the chest acceleration with (dash-dotted) and without (solid) prior knowledge of the crash pulse. Right: Relative chest displacement

C. Closed loop MADYMO results

The reference governor is now applied to a primal compensated system, as shown in Fig. 3. The occupant model consists of a 50%-ile Hybrid III dummy from the MADYMO database, in which the conventional belt load limiter is replaced by a belt force actuator. The occupant is seated in a seat in a compartment model, which includes a driver airbag. The controller consists of an integrator with appropriate gain and is designed such that the chest acceleration tracks a setpoint r. For more details on this model, see [21], [16].

Results for the controlled chest acceleration for the setpoint from the RG are shown in figure 7 together with the required belt force. Results are compared to responses from an identical occupant model with a conventional restraint system, i.e. a 4kN load limiter, which is obviously uncontrolled. One can see that the $A_{\max}$ criterion has reduced by approximately 60%. To emphasize the interest of these results, note that that the only inputs to the RG algorithm is the initial vehicle velocity v_0 and the measured vehicle acceleration at the current time, $a_{\text{veh}}(t_c)$. On the contrary, it should also be mentioned that this injury reduction is achieved with an ideal belt actuator and perfect sensors, which of course will not be realizable.

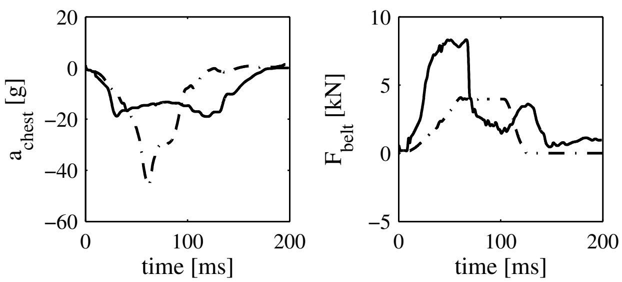

Fig. 7. Chest acceleration (left) and belt force (right) responses from a system with a conventional restraint (dash-dotted) and a closed loop controlled system with a Reference Governor (solid)

VI. Discussion and future work

In this paper, a novel control strategy for real-time controlled belt restraint systems is proposed, based on reference management. The control method consists of a combination of a primal control loop using conventional tracking and a modified reference governor (RG). The RG finds an optimal setpoint for the chest acceleration while satisfying constraints and without having prior knowledge of the upcoming crash. The RG control strategy is believed to be an important step towards real-time implementation of controlled passive safety systems.

When accurate pre-crash information systems become available, e.g. on closing speed or impact angle, the vehicle motion prediction can significantly be improved without fundamentally changing the algorithm. This will increase the performance of the overall control scheme, as this has to be less robust to prediction errors. In this paper, only a single injury criterium is minimized although the method can be extended to multiple injury criteria [22].

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