Motorcycle Accident Reconstruction
Part II - Self Learning Models

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ABSTRACT

In this paper a self learning method, based on Abductive Networks, is being used for the development of a model that related pre-impact motorcycle speed to post-impact measurable data. The best results were obtained where the motorcycle wheel base reduction and the maximum crush of the vehicle were used as input the model. This result is, to some degree, similar to the results obtained in previous paper where these two parameters were assumed to be linearly related to the motorcycle pre-impact speed.

Keywords

Motorcycle Accident Reconstruction, Accidents Reconstruction, Motorcycle Accidents.

1. INTRODUCTION

The increasing number of motorcycle accidents is a major concern to policy makers. The understanding the causes of this accidents by accident reconstruction tools, will allow law makers to address this issue by regulating design features, safety requirements, road design modifications etc.[1].

Different models, based both vehicle damage and on on-site measurements, were reported in literature [2-9]. Some are based on physical principle like conservation of linear and/or angular momentum, and some based on correlation between measurable data. In both cases the results are not satisfactory in part due to the fact that very few crash tests are performed on motorcycles.

The method described in this paper falls into the second category where a correlation between measurable data and the motorcycle's pre-impact speed is being searched. Previously, a specific model was assumed and then the measured data was correlated to it. Thus, the produced models were not necessarily the best ones and mostly simple as linear polynomials. In this case, a self learning method is being used which automatically will find the best model that will fit the data. As a result higher order polynomial might be found. In any case it should be emphasize that since the model are "just" correlation to measured data they do not shed any light on the physics of the crash.

This self learning method, which will be described in the following section, is called "Abductive Networks. This method was used successfully in many application one of which was to determine impact force and crush energy in vehicle collisions [10].

2. AIM – ABDUCTIVE NETWORKS

AIM [11] is a powerful supervised inductive learning tool for automatically synthesizing network models from a database of input and output values. The model emerging from the AIM synthesis process is a robust and compact transformation implemented as a layered abductive network of feed-forward functional elements as shown in Figure 1.Figure 1

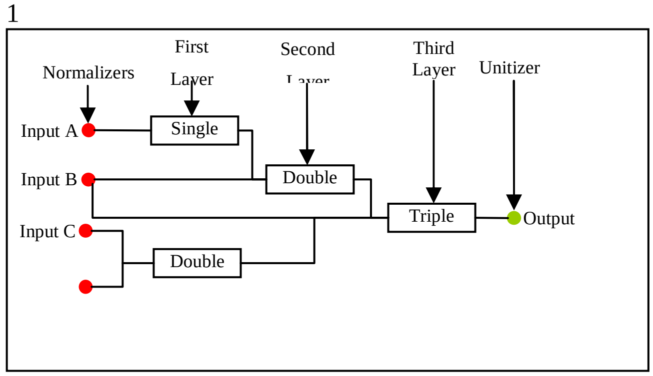

Figure 1: Example of Abductive Network.

All the functional and connection elements are learned from the input data. Currently AIM has seven types of elements.

The algebraic form of each element is a polynomial where W_n are the coefficients determined by AIM and X_n are the input variables (Table 1 shows sample elements). All terms in an element's equation may not appear in a node since AIM will throw out or carve terms which do not contribute significantly to the solution.

Table 1: Example of elements definition.

Single	$W_0 + W_1 * X_1 + W_2 * X_1^2 + W_3 * X_1^3$
Double	$W_0 + W_1 * X_1 + W_2 * X_2 + W_3 * X_1^2 + W_4 * X_2^2 + W_5 * X_1 * X_2 + W_6 * X_1^3 + W_7 * X_2^3$

The eligible inputs for each layer and the network synthesis strategy are defined in a set of rules and heuristics which are an inherent part of the synthesis algorithm.

AIM automatically determines the best network structure, element types, coefficients and connectivity by minimizing a modeling criterion which attempts to select as accurate a network as possible without over fitting the data. The modeling criterion used within AIM is the Predicted Squared Error (PSE). The PSE is a heuristic measure of the expected network squared error for independent data not in the training database. The PSE is given by:

$$PSE = FSE + KP \tag{1}$$

where FSE is the fitting squared error of the model to the training data and KP is a complexity penalty term determined in AIM by the equation:

$$KP = CPM * \frac{2K}{N} s_p^{\,2} \tag{2}$$

where K, N and s_p^2 are determined by the database of examples used to synthesize the network and CPM, the Complexity Penalty Multiplier, is a variable the user can select. The default value of CPM is 1; a lower value decreases the complexity penalty impact and results in a more complex network and inversely for a higher value.

To create a model using AIM one has to follow these steps:

1. Decide what are the inputs and the output of the model.
2. Create a database which includes sets of inputs and the corresponding outputs from the process being modeled.
3. Train the abductive network using the above database.
4. Evaluate model performance of the model using sets of inputs/outputs which were not used to train the network.
5. Once the network (model) performs to satisfaction an explicit model can be derived and implemented.

3. THE DATA SETS AND DATA ALLOCATION

Two data sets with experimental data were available to the authors:

1. Data Set I: contains data from 47 crush tests that were performed by previously different investigators.

2. Data Set II: contains data from 13 crush test that were performed by the authors.

Both data sets include the following information:

a) Pre-collision motorcycle's speed (V_M).

b) Motorcycle's wheelbase reduction due to the impact (W_R).

c) Vehicle's maximum crush (see Figure 2) (D_C).

d) The impact location with the car, "Hard" or "Soft" locations. "Hard" location is considered as a location 3" from a pillar or axle and a "Soft" location is any other place on the car (e.g. doors or fenders) (*H* or *S*).

e) The weight of the motorcycle (W_M).

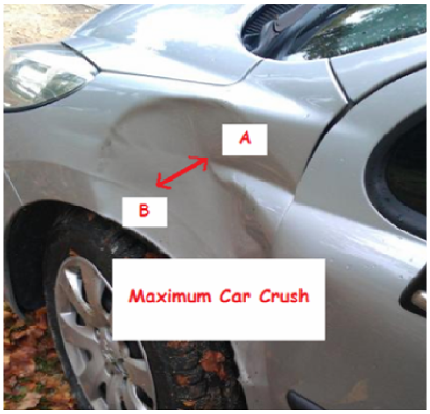

Figure 2: Vehicle's maximum car crush.

As mentioned before, the first step is to "train" the system by providing a set on input and the corresponding outputs to the system. The inputs are post impact measurable quantities such as motorcycle's wheelbase reduction. The output, in the particular case, is only the pre-collision motorcycle's speed. The training data set is selected randomly from the entire data set. Once a model is established (the network converged), the rest of the data is used to evaluate the prediction achieved by the model.

4. MODELING

Model # 1

This model relates to the model proposed in [2] where the motorcycle's pre-collision impact speed was related only to its wheelbase reduction. Thus, the only input to this model is the wheelbase reduction of the motorcycle (W_R) and the only output is the speed. The model has been trained using measurements from 24 different crash tests from Set I.

Upon convergence, the model was used to predict the motorcycle speed of the other 23 crash tests, from the same set, which were not used for training. The average error of the predicted speed was 8.45% and the maximum error was 23.8%.

At this point the model was used to predict the motorcycle's speed user data set II. The average prediction error was 17.8%.

This first model was more of a test to see how the prediction would be using only one variable and training the model with the data set #1. It's surprisingly successful as the average errors are under 20%.

Model # 2

This model relates to the model proposed in [2] where the motorcycle's pre-collision speed (V_M) was related to its wheelbase reduction (W_R) and the maximum crush of the car (D_C). Again, 24 different crushes, which were selected randomly, used to train the network. Once the model was obtained, upon convergence, an explicit formula can be extracted:

$$V_M = 13.48 + 2.05W_R + 0.40(D_C) + 0.038(D_C)^2 \quad (3)$$

The capability to obtain an explicit relationship is very advantageous compared to other self-learning methods. For example, we can determine the sensitivity of the speed prediction to the errors in the measurements of the wheelbase reduction and the vehicle's maximum crush:

$$(\Delta V_M) = \frac{\partial(V_M)}{\partial(W_R)}(\Delta W_R) + \frac{\partial(V_M)}{\partial(D_C)}(\Delta D_C) \quad (4)$$
$$(\Delta V_M) = 2.05(\Delta W_R) + 0.40(\Delta D_C) + 0.076(D_C)(\Delta D_C)$$

where: *(ΔV_M)* – Error in motorcycle's speed

(ΔW_R) – Error in the measurement of the motorcycle's wheelbase reduction

(ΔD_C) – Error in the measurement of the vehicle's maximum crush

As an example assume that *(ΔW_R) = (ΔD_C) = 0.25*". It will result:

$$(\Delta V_M) = 0.6125 + 0.019(D_C) \quad (5)$$

Eq. (5) indicates that the error in the prediction of the motorcycle's speed is linear with the value of the vehicle's maximum crush measurement. Meaning that during the accident reconstruction process this value has to be measure with high accuracy.

The model was used to predict the motorcycle's pre-impact speed of the other 23 cases in data set #1. The errors in the predictions of the motorcycle's speed had average of 4.64% and the maximum of 11.47%.

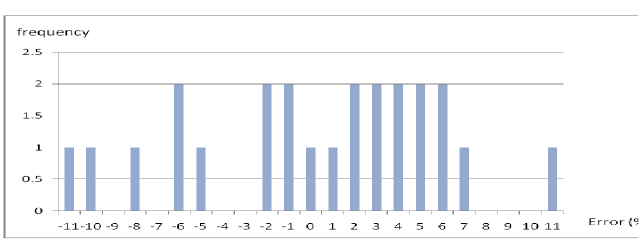

Figure 3: Histogram of the errors in prediction of the motorcycle speed using data set I.

The same model was used to predict the motorcycle's pre-impact speed of the cases provided in data set II. It resulted in an average error of 12.8% and maximum error of 22%. The histogram of these prediction errors are shown in Figure 4.

Other Models

Few other models, which differ from each other by: 1) The set of inputs; 2) Inputs configuration; and 3) Training sets, were tried (see Table2). Observing the results given in Table 1, one can reach the following conclusions:

1. One the training data and the verification data are from the same data set, the models are better (smaller errors)(tests 1,2 5,6 and 7).
2. Some set of input produces better results (within the same set). Compare the results of models 1 and 2 and 5 and 6.
3. The fact that the mixed data set produced relatively inferior results is that the tests were probably controlled differently.

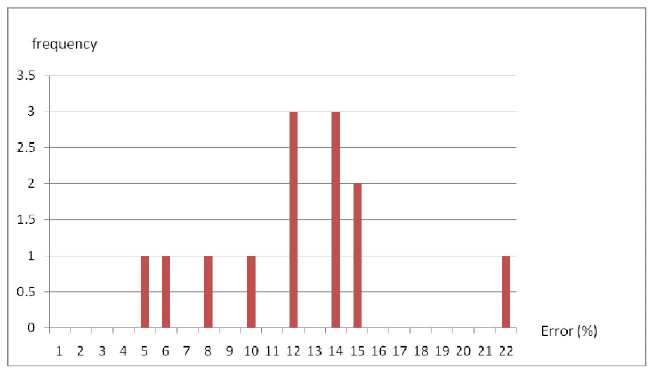

Figure 4: Histogram of the errors in prediction motorcycle's speed using model #2 and data set II

Table 2: Other models

	Inputs	Data Set I		Data Set II	
		Average Error [%]	Max. Error [%]	Average Error [%]	Max Error [%]
1[1]	(W_R),(D_C), (H) or (S)	4.24	11.6	25	
2[1]	(W_R),(W_M)	6.27	21.74	23	
3[2]	(W_R),(D_C)	5.61	20		
4[2]	(W_R),(W_M)	7.49	17.42		
5[3]	(W_R),(D_C)	59.78		8.64	13.69
6[3]	(W_R),(D_C)	48	102	1.89	7.63
7[1]	(W_R),(D_C) (W_M)	6.94	17.92	180.47	

(1) Training with data set I

(2) Training with a mix from both data sets

(3) Training with data set II

4. CONCLUSIONS

A simple self learning model for the estimation of a motorcycle's pre-impact speed was presented. The model is not physical model and is based on the correlation of experimental data to the motorcycle speed. It was obtained automatically using the AIM system and it is reasonably accurate. The model is explicit in contrast to non-explicit model that can be obtained by other learning procedures such a Artificial Neural Networks. As such it provides better understanding to the effect of each measurement on the model and to the sensitivity of the model to each of the inputs.

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