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Improvement of perceived vehicle performance through adaptive electronic throttle control

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Abstract: With the advent of production electronic throttle control there is scope for increased customer satisfaction through the optimization of the throttle pedal demand map to individual drivers. The aim of this study is to develop algorithms to identify, from variables measured in real time on a test vehicle, the requirement for and the direction of adaptation of throttle pedal progression. An on-line appraisal procedure has been developed to identify the individual 'ideal' progression (IIP) for any driver. During the appraisal the subject is exposed to a series of pedal progressions, and their verbal response to each change is used to converge to their optimal setting. Vehicle data acquired on these appraisal drives have been regressed against IIP in a full factorial study, and the most statistically significant driver model established. A preliminary implementation of the model is used to demonstrate that throttle progression adapts appropriately towards IIP, thereby matching vehicle performance feel to driver expectations.

Keywords: adaptive throttle, drive appraisals, electronic throttle control, model regression, pedal progression, performance feel

NOTATION

a, b, c, d	system coefficients	M_1	slope of straight-line model, fitted below the model maximum
$\hat{a}, \hat{b}, \hat{c}, \hat{d}$	digital filter transformed coefficients	M_2	slope of straight-line model, fitted above the model maximum
ARMA	autoregressive moving average	MRV	model regression variable
b_k	subdivision of the range (75th percentile algorithm)	n	number of progression steps tested within a given iteration in the appraisal
CBM	customer behaviour model	n_p	number of data points
dT/dD	rate of change in torque with pedal demand	P	pedal gain (no units)
dT/dN	rate of change in torque with engine speed	P_{\max}	maximum pedal gain (no units) within the appraisal
D	pedal demand (per cent)	P_{MAX}	maximum pedal gain (no units)
D_t	pedal demand at time t (per cent)	P_{\min}	minimum pedal gain (no units) within the appraisal
D_{t-1}	pedal demand at time $t-1$ (per cent)	P_{MIN}	minimum pedal gain (no units)
f_1, f_2, f_3, f_4	factorial parameters measured on the vehicle	Q_3	75th percentile
$H(s)$	general system	$Q_{3\text{POSN}}$	position of the 75th percentile
i	candidate rating number	r	candidate rating (unitary)
IIP	individual ideal progression	R	returned Pearson error matrix (no units)
IIP_i	concatenated x for all candidates	\bar{R}_w	mean Pearson correlation coefficients with model regression variable i included in the regression
j	test point	\bar{R}_{wo}	mean Pearson correlation coefficients with model regression variable i excluded from the regression
k	number of experiment	s	poles of $H(s)$
		sgn	signum function

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S_j	candidate rating correlation score (no units)
SSV	steady state value
t	time (s)
\mathbf{u}_i	regression matrix for model regression variable k
$U(k)$	P input at iteration k (no units)
$U(k-1)$	P input at iteration $k-1$ (no units)
WOT	wide-open throttle
\mathbf{x}	individual ideal progression vector, of length k
x_k	model regression variable k
y_i	individual ideal regression model
$Y(k)$	filter output at iteration k (no units)
$Y(k-1)$	filter output at iteration $k-1$ (no units)
ZOH	zero-order hold
$\alpha, \beta, \gamma, \delta, \varepsilon$	least-squares coefficients of the customer behaviour model
α_i	significance of model regression variable i
α_k	general least-squares fitted coefficients
ε	unfitted error (least-squares regression)
λ	range reduction factor (no units)

1 INTRODUCTION

Motor manufacturers continually strive to improve the product they offer to the motoring public. In the last two decades much of their effort has been directed towards identifying the precise needs and wishes of customers and then successfully transferring these to their product. One area to have received attention is the perceived performance of the vehicle. In this case the manufacturers have been limited to identifying the optimum set-up to satisfy all drivers. Passmore [1] and Passmore *et al.* [2] reported one such study. They carried out an extensive factorial study of performance feel, investigating factors, effects and interactions. The conclusions gained from the study are that, although actual wide-open throttle (WOT) acceleration is the primary parameter in giving good performance feel, secondary effects also have a powerful effect, and in particular the throttle progression (rate of change in torque with pedal demand, dT/dD) and rate of change in torque with engine speed, dT/dN .

The study identified the optimum set-up for throttle progression and dT/dN but also showed a high variance in response from drivers and some evidence of demographic effects, which lead to the conclusion that performance feel benefits could be achieved if a vehicle's throttle system were able to adapt to the driver's preference. The advent of production electronic throttle control makes this a possibility and is the subject of this

paper. This work details the development of an on-line adaptive throttle control system to meet these customer needs. At this stage a fully mapped system would be difficult to implement; therefore, to simplify the development, inference from Passmore [1] indicates that the first parameter to be considered in a one-dimensional system should be throttle progression. The primary aims of this study are to develop algorithms to identify, from parameters measured in real time on the vehicle, the requirement for and the direction of adaptation of the throttle progression and to implement these algorithms in a working system.

To implement such a system requires a model of driver satisfaction that can be evaluated in real time. To establish this 'customer behaviour model' (CBM) the individual ideal progression (IIP) for each driver needs to be identified. Thus a novel appraisal method has been developed to identify IIP accurately, using a series of iterative paired comparisons, implemented in an automated double-blind randomized block design process on the test vehicle. This method is described in section 2 of the paper. Measurements such as engine and vehicle speed are acquired during the appraisal, and a subset of these are linearly combined to generate a CBM model, described in section 3. Section 4 describes a statistical analysis to determine the most significant subset of variables to employ in the model, and the paper concludes with field trials of the final CBM, used to adapt progression in the test vehicle.

2 IDENTIFICATION OF THE INDIVIDUAL IDEAL PROGRESSION (IIP): THE 'EYE TEST' METHOD

The 'traditional' format of appraisal testing using, for example, the Loughborough Likert scale (cf. reference [1]), although well established and highly regarded, is inefficient at returning a reliable measure of IIP in a suitably short (less than 2 h) time frame. Such methods require the driver to give ratings following each (typically fixed-length) test drive; this restricts the number of options that can be tested and relies on the fact that the driver has a good memory of what was good or bad. (It should be noted that the driver is unaware of the precise nature of the vehicle performance modification that is being made during the appraisal.) The goal here is to achieve testing which:

- exposes the driver to a wide range of operating conditions (progressions),
- identifies the range of progressions over which a given driver is insensitive to change,
- can be carried out over a single test drive, within the concentration span of the driver (ideally no more than 1 h),

- (d) is robust to the limitations of the driver's rating consistency,
- (e) is robust to 'incorrect' responses caused by changing environmental conditions and
- (f) does not follow predictable patterns of change which might bias the driver's expectations and hence responses.

The solution described here uses paired comparisons to limit the concentration and rating skills required by the driver. The candidates are asked to state their preference to the current progression, giving an answer of better, same or worse than the previous setting. Also, the driver is allowed as much or as little time as he/she requires to make the assessment; this has risks in terms of (e) above but reaps considerably greater benefits in terms of (a) to (d). A degree of randomness in progression selection, together with automated (and hence 'double-blind') testing then ensures that (f) is satisfied.

2.1 Detailed appraisal methodology

Progression in this study is defined as an application of gain to the input-output relationship of the throttle pedal; thus

$$\text{Throttle cable travel} = P \times \text{pedal position} \quad (1)$$

Initially, prototyping was carried out to identify the safe limits of progression over which the 'eye test' could operate. These limits were found by taking the test vehicle out, and changing the progression until the vehicle became undrivable:

Lower limit $P_{\text{MIN}} = 0.5$

Upper limit $P_{\text{MAX}} = 3.5$

The lower limit might be justified even though it restricts maximum throttle opening to half WOT. It has been

observed that some drivers do not even use full pedal travel in a conventional ($P = 1$) situation, indicating that they do not wish to use the full power of the engine, at least during the (B class road) driving environment tested. The lower limit maximizes controllability but, below this progression peak, torque is reduced to the point where the car is undrivable. The upper limit is defined by the point beyond which the car becomes uncontrollable, due to the very small amount of pedal travel to WOT. Gains of $P > 1$ are saturated at WOT.

An initial range is selected within these limits, which covers most of the 'expected' IIPs as determined in previous appraisals. n individual test points are then defined in this range by dividing it into $n - 1$ equally spaced steps.

The process is then to record a rating between each pair of adjacent points, while attempting to minimize the predictability of the changes. This is achieved by randomly setting n as either $n = 5$ or $n = 7$ and then subdividing the range into two. The order of execution of each half, and the direction of travel (increasing or decreasing P) with each half is also randomized. This is illustrated in the example shown in Fig. 1. The order of tests is shown by $\underline{1}$ to $\underline{8}$; therefore the ratings are recorded in the order a to f. (The second half of the range is tested first with increasing P , followed by the first half with decreasing P .) Note that, although a rating is requested between all changes in progression, the comparison between tests $\underline{4}$ and $\underline{5}$ is ignored, as is that between test $\underline{8}$ and the first test in the next iteration of the algorithm. Further randomness in test ordering is avoided to limit the number of these unproductive comparisons. Each of the ratings is recorded as follows:

- $r = +1$: better than the last setting
- $r = 0$: the same, or insignificant change compared with the last setting
- $r = -1$: worse than the last setting

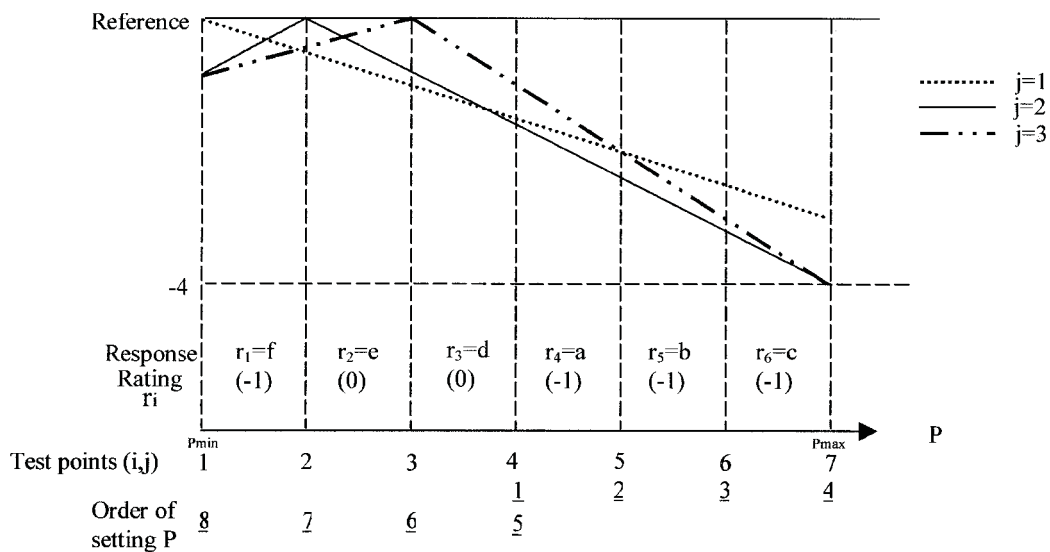


Fig. 1 Example of eye test slope estimation

Using these ratings, a piecewise linear model is fitted about each of the n tested progressions in turn, in order to locate the maximum (or exceptionally, the minimum) point of preference (see Fig. 1). For each candidate model, the peak is assumed to be at the j th point, and slopes are calculated about that point. The slope of the first line is determined from the ratings r_i as

$$M_{1(j)} = \frac{\sum_{i=1}^{j-1} r_i / \Delta P_i}{j-1} \tag{2}$$

where

$$\begin{aligned} \Delta P_i &= P_{i+1} - P_i \text{ if the test order has } P \text{ increasing} \\ \Delta P_i &= P_i - P_{i+1} \text{ if the test order has } P \text{ decreasing} \end{aligned}$$

The second slope is then given as:

$$M_{2(j)} = \frac{\sum_{i=j}^{n-1} r_i / \Delta P_i}{n-j} \tag{3}$$

Note that M_1 is not calculated when $j=1$, and M_2 is omitted when $j=n$.

The optimal model is then selected as that which best fits all ratings, according to a correlation score S_j :

$$S_j = \sum_{i=1}^{j-1} r_i \operatorname{sgn}(\Delta P_i M_{1(j)}) + \sum_{i=j}^{n-1} r_i \operatorname{sgn}(\Delta P_i M_{2(j)}) \tag{4}$$

Figure 1 also illustrates the line fitting defined by this process for the first three values of j ; by inspection of the r_i , the best fit should be obtained at either $j=2$ or $j=3$, and this is confirmed by the correlation scores $S_1=3$, $S_2=S_3=5$. In cases such as this, where two scores are equal, the point closest to the midpoint of the range is taken ($j=3$ in this case).

When the optimum point of the current range has been found, the process above is iterated, with the

next set of tests centred on this optimum, and the range reduced by a factor λ , defined according to the correlation score achieved:

$$\lambda = 1 - 0.5 \frac{\max(S_j)}{\sum_{i=1}^{n-1} |r_i|} \tag{5}$$

Thus the search converges if consistent ratings are given.

Obvious adjustments are made to keep the testing within the bounds $P_{\text{MIN}} \leq P \leq P_{\text{MAX}}$ and the one exception to the rates given above is where the gradient search finds a minimum ($M_1 < 0$ and $M_2 > 0$). This result indicates very poor driver consistency but, if it occurs, testing continues by centring the new range on $j=1$ or $j=n$ depending on which of M_1 or M_2 is best correlated, according to the appropriate single term of S in equation (4). The candidate drives repeated iterations of this process until convergence is indicated by a consistent set of $r_i = 0 \forall_i$.

In Fig. 2, the eye-test method is illustrated in simulation. A polynomial curve was used to represent IIP (peaking at $P=0.916$) and to choose r_i values ($r_i=0$ where the change in the polynomial is less than 1). With completely consistent responses (Fig. 2a) the eye test predicts that $P=0.916$, but the algorithm also performs very well in the face of significant disturbance. Figure 2b shows a test with 12 of the $26r_i$ randomly (and wrongly) chosen, and the final result is $P=0.899$.

In field trials the eye test appears to be successful, with all candidates saying that the final vehicle response was an improvement over the standard setting. Unexpectedly the general trend was that, the more subjectively aggressive the driver, the lower is the IIP that was preferred. This indicates that a more aggressive driver prefers (or requires) more control over the available power.

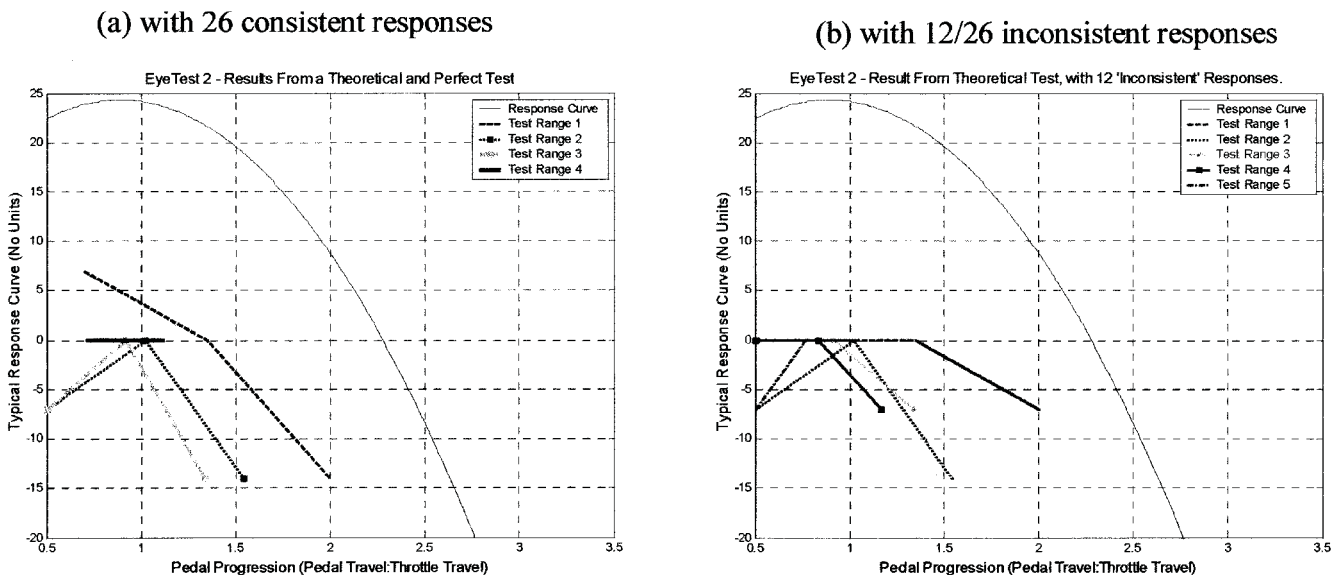


Fig. 2 Eye test simulation results: testing robustness

3 DEVELOPMENT OF A CUSTOMER BEHAVIOUR MODEL (CBM)

Once the IIPs for a sample have been identified, a method is needed to correlate these with the driver's behaviour in so far as this can be measured in the vehicle. The behaviour model is constructed from variables sampled in real time on the vehicle, and from filtered variants of these. The 'eye-test' appraisal has a 'free driving format' [2], driven over predetermined B class roads using the Ford Focus 2.0l test vehicle. For this reason, data sampled from the vehicle during the appraisal can be used to correlate with the final IIP found. These data are ideal for two reasons:

1. They properly reflect the driver's mood during the appraisal; this is known to have an influence on IIP.
2. A wide range of different progressions are being executed throughout the data; therefore the influence of progression on the variables measured is minimal.

Table 1 illustrates the raw data acquired during the tests. From these, a relatively slow ARMA is also deduced (having a settling time of around 1200 s), and a 75th percentile measure Q_3 is also derived, using a memory and processor efficient algorithm which is described in the Appendix.

Note that the pedal rate is calculated using a backward-difference approximation, from pedal demand D :

$$\frac{dD}{dt} = \frac{D_t - D_{t-1}}{t_t - t_{t-1}} \quad (6)$$

Seven raw data signals are thus derived from just four sensors, and these are manipulated to provide 28 different continuous variables, giving both rapidly and slowly varying measures of driving style. These 28 MRVs can be united in various combinations in an attempt to provide a model for IIP, using multiple linear regression. The regression is carried out using a least-squares fit, returning a model of the form shown in the following equation:

$$y = \hat{\alpha}_0 + \hat{\alpha}_1 x_1 + \hat{\alpha}_2 x_2 + \dots + \hat{\alpha}_k x_k + \varepsilon \quad (7)$$

where

- $y = \text{IIP}$
- $\alpha_k = \text{least-squares fitted coefficients}$
- $x_k = \text{MRV}_i$
- $\varepsilon = \text{unfitted error}$

Figure 3 shows a sample regression using three MRVs. There are 12 candidates represented in the plot, with the x axis relating to the time on a test drive. Each candidate has an equal amount of time represented.

Figure 3 indicates that distinct differences exist between drivers, demonstrating that a suitable customer model might be defined. Thus a statistical experiment was conducted to identify an accurate CBM, using a small number of MRVs.

4 STATISTICAL ANALYSIS TO DETERMINE THE BEST MODEL

A factorial experiment is a well-known applied statistical method used to consider all possible combinations of variables in a multiple linear regression model. To cover all possible combinations of all variables, 2^k tests would be performed. As 28 variables have been defined for testing, 2^{28} tests would need to be performed. As this would take approximately 466 days, a more efficient

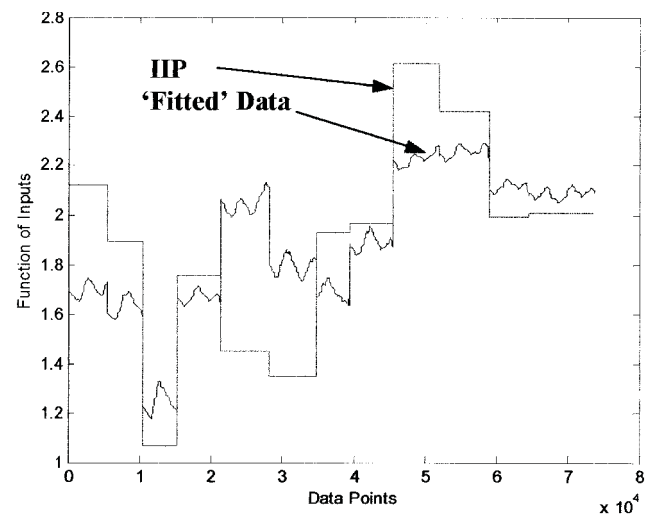


Fig. 3 Sample regression of MRVs to IIP

Table 1 Model regression variables (MRVs)

Global variable	Raw signal	ARMA*	Q_3	Q_3 ARMA*
Engine speed	×	×	×	×
Engine speed at gear change-up point	×	×	ZOH† (not Q_3)	ZOH ARMA*†
Absolute lateral acceleration	×	×	×	×
Longitudinal acceleration	×	×	×	×
Throttle pedal position	×	×	×	×
Throttle pedal rate	×	×	×	×
Vehicle speed	×	×	×	×

* ARMA, autoregressive moving average.

† ZOH, zero-order hold.

design was needed! The method adopted was to randomly split the variables into two 14-variable factorial tests. From these two separate experiments the 14 most significant variables were then tested in a third factorial experiment and the results of this experiment used to produce the final model.

For each regression in the factorial experiment a Pearson correlation coefficient is calculated measuring the extent of the linear fit of the model; thus the factorial experiment has the form

$$[\mathbf{R}] = \left[\frac{n_p \sum x(\mathbf{u}_i y_i) - \sum x \sum \mathbf{u}_i y_i}{\sqrt{[n_p \sum x^2 - (\sum x)^2][n_p \sum (\mathbf{u}_i y_i)^2 - (\sum \mathbf{u}_i y_i)^2]} \right]_{i=1}^{i=k} \quad (8)$$

where

$$y_i = (\mathbf{u}_i^T \mathbf{u}_i)^{-1} \mathbf{u}_i^T x$$

$$\mathbf{u}_i = \begin{bmatrix} 1 & x_1(t_0) & \dots & x_i(t_0) \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_1(t_n) & \dots & x_i(t_n) \end{bmatrix}$$

$$x = \begin{bmatrix} \text{IIP}_1 \\ \vdots \\ \text{IIP}_i \end{bmatrix}, \quad \text{IIP}_i = \begin{bmatrix} \text{IIP}_{n_{pi}} \\ \vdots \\ \text{IIP}_{n_{pi}} \end{bmatrix}_{n_p=1}^{n_p=k}$$

where

- k = number of experiments
- t_n = datum at time t
- \mathbf{R} = returned error matrix
- n_p = number of data points

This was evaluated for $k = 2^{14}$ experiments covering all possible combinations of half of the MRVs. The returned error matrix \mathbf{R} can now be analysed to identify the most significant model. The significance of an individual MRV

was calculated using

$$\alpha_i = \bar{R}_w - \bar{R}_{wo} \quad (9)$$

where

- α_i = significance of MRV _{i}
- \bar{R}_w = mean Pearson correlation coefficients with MRV _{i} included in the regression
- \bar{R}_{wo} = mean Pearson correlation coefficients with MRV _{i} excluded from the regression

If none of the MRVs is statistically significant in providing the ‘best’ model, the significance values α_i will be randomly distributed. This can be clearly illustrated using the convenient graphical technique of normal score plotting, where in the case of purely random data the normal plot approximates a straight-line graph, whose slope is defined by the standard deviation (see, for example, reference [3]). Conversely, statistically significant MRVs appear as deviations from this straight line, and the degree of deviation illustrates the level of significance.

Figure 4 shows the results for single-variable regressions from the two initial factorial experiments. Eight of the MRVs have positive significance which is above the ‘noise’ level; these are (coincidentally) the values with a normal score greater than 0.5. Of these, three have major significance.

The eight positively significant MRVs were then combined with six other, randomly selected MRVs, to conduct a final factorial experiment. Figure 5 shows the results, and here the significance values of all possible combinations of up to four MRVs are illustrated.

As can be seen, there is obvious deviation from the straight line, with several combinations of four MRVs being statistically significant. Of these, all should provide good models of customer behaviour but, from an operational point of view, only those that have a large

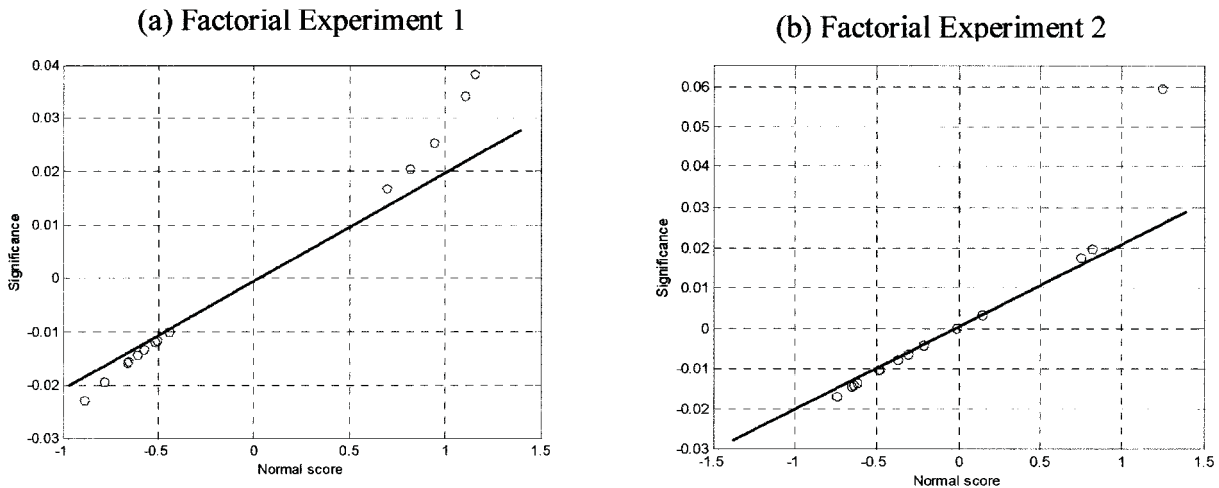


Fig. 4 Initial factorial experiment results for a single fitted MRV

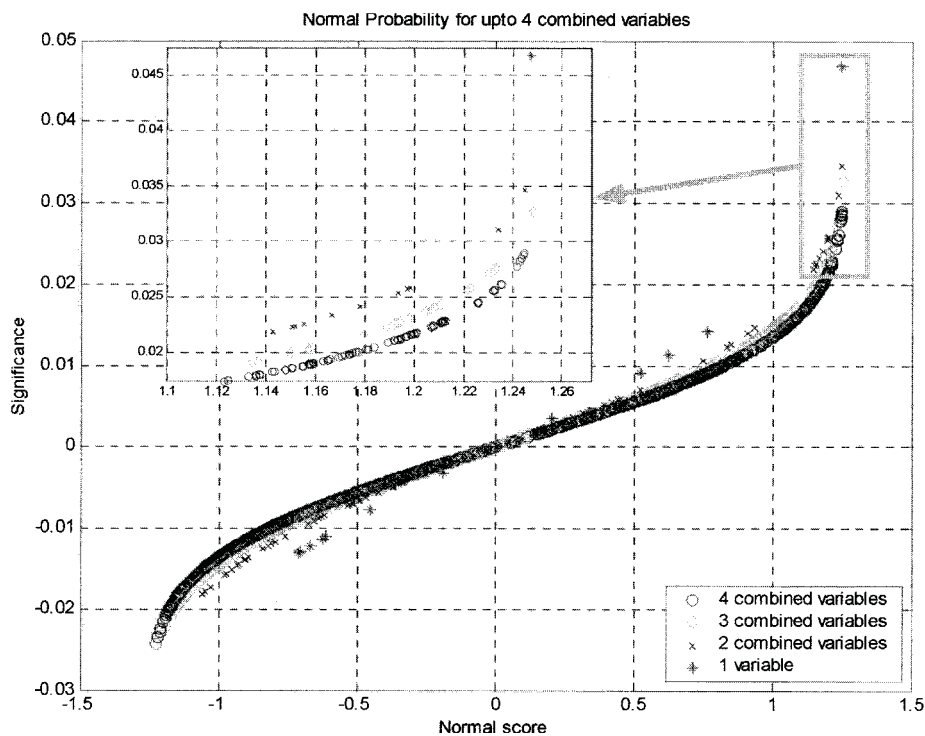


Fig. 5 Normal score plot for final factorial experiment

magnitude are considered further. Note that, in the figure, models with fewer MRVs *appear* more significant; these are not more accurate, however, as the plot omits the mean level of significance, which is lower for a lower number of MRVs. It should also be noted that the use of more than four MRVs in the CBM *will* result in a better fitting model, but that the overall statistical significance would be reduced. The 'perfect' model could be generated if enough parameters were used, but this would be a model that is a 'forced' fit of the particular test data seen here and not a general reflection of customer behaviour.

4.1 Final customer behaviour model

Results of the factorial experiment show that the CBM for pedal gain should take the form

$$P = \alpha f_1 + \beta f_2 + \gamma f_3 + \delta f_4 + \varepsilon \quad (10)$$

where the parameters f_1 , f_2 , f_3 and f_4 are defined by the factorial experiment and the coefficients α , β , γ , δ and ε are calculated using least-squares theory.

Figure 6a shows the final behaviour model regression, which exhibits a 95 per cent correlation between the 'ideal' progressions and the resultant model. Although none of the 'ideal' progressions is met exactly, 11 of the 12 candidates are within $P = 0.2$ of their IIP. In general, candidates were found to be insensitive to a small change in progression; therefore, the model is considered acceptable. Figure 6b shows the influence of each parameter

on the final result; this shows the relatively even significance of each parameter in the model. The definition of a suitable CBM now allows the implementation of a prototype auto-adaptive electronic throttle control algorithm.

5 APPLYING THE MODEL TO ON-LINE ADAPTIVE THROTTLE CONTROL

Figure 6a highlights that, although the general fit of the model is good, allowing the model to run directly on the vehicle would lead to rapid local changes in pedal progression. The final output of the pedal gain is thus controlled by a first-order low-pass digital filter. This smooths out local variations and also allows the rate of adaptation to be controlled. Defining the general system as

$$H(s) = \frac{as + b}{cs + d} \quad (11)$$

the coefficients are set at a suitable level such that rate control and noise filtering are optimal. To ensure that the system adapts to the correct level [i.e. steady state value (SSV) = 1], the final value theorem is applied. In this case $a = 0$, $c = 1$, and b and d are equal, defined to give a slow response rate.

To define the filter in a suitable format, such that $Y(k)$ can be obtained, the inverse Laplace transform of the 'z transform' (applied using the 'Tustin' or trapezoidal

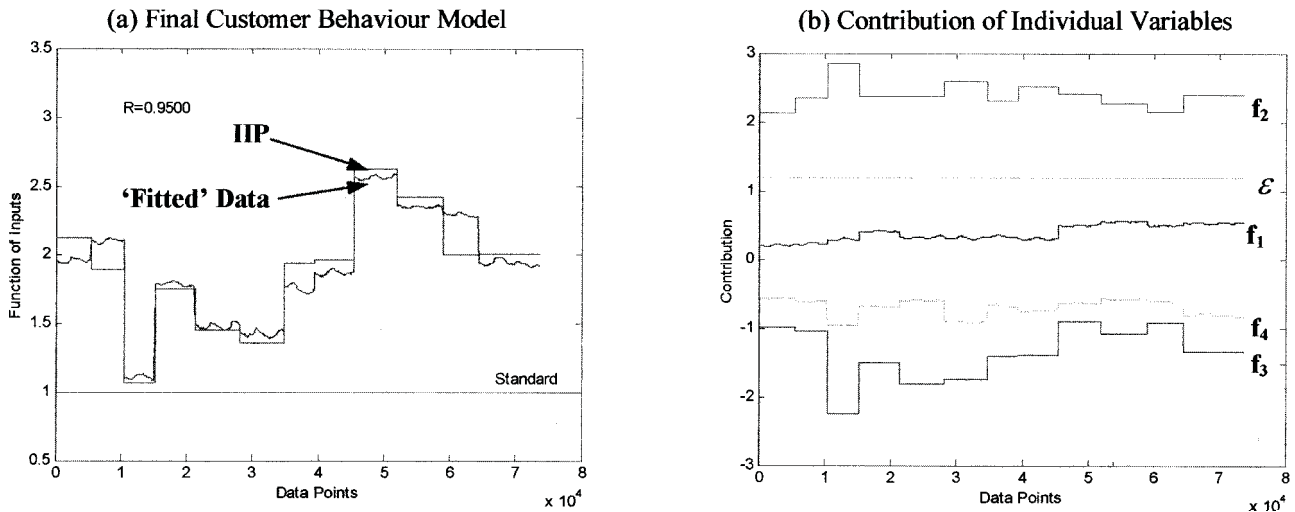


Fig. 6 Final CBM fit for all candidates, and significance of individual parameters

approach [4]) is taken; thus, the final filter has the form

$$Y(k) = \frac{\hat{a}U(k) + \hat{b}U(k - 1) - \hat{d}Y(k - 1)}{\hat{c}} \quad (12)$$

Only slow adaptation rates have been considered thus far, to allow sufficient analysis of the system to be carried out, and to respect safety issues before extensive analysis of the adaptation rate has been completed.

5.1 Off-line results

Figure 7 shows the result of a simulation of the adaptive system, using data recorded during the eye-test appraisal. A start point of $P = 1.5$ has been used for the simulation. The final adapted value correlates well with $IIP = 1.993$. The gain is not held constant for the full simulation of the drive, as the behaviour may change over time. The result signifies that the algorithm is suitable for field testing.

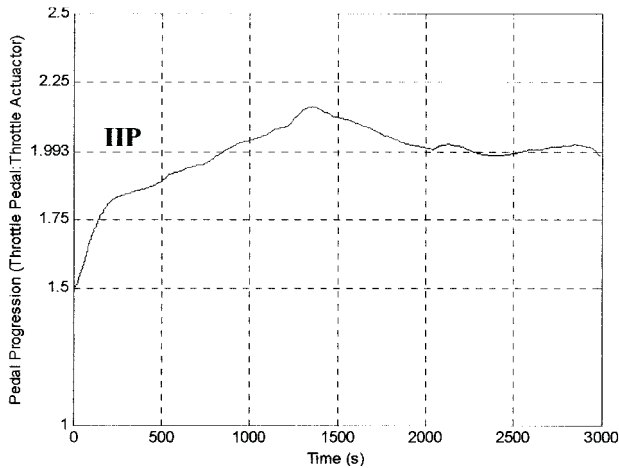


Fig. 7 Adaptation simulation of an eye test candidate

5.2 On-line results

Figure 8 shows that there is good correlation between the direction of adaptation and IIP, $P = 1.352$ in an on-line implementation. The IIP found in the eye-test appraisal is not necessarily correct for that driver on the day of testing, it was only correct at the time of the eye test. IIP is dependent on influential factors on driving style, such as driving conditions, traffic, driver mood and time of day. Indication that the process was adapting to a suitable level was given by the fact that the driver was happier with the vehicle at the end of the driving period than at the beginning.

6 CONCLUSIONS

A novel on-line procedure has been developed to identify optimum or 'ideal' progression for any driver (the IIP). This procedure is a paired comparison technique labelled

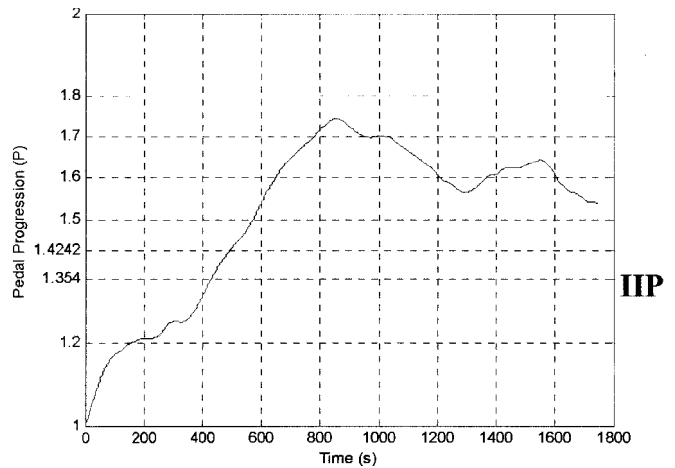


Fig. 8 Time history of pedal gain during a field trial

the eye test. The procedure has developed a number of significant conclusions:

1. The novel methodology provides a reliable robust method for obtaining customer IIPs.
2. The eye-test method provides a useful tool through which a vehicle can be tailored to particular customer needs, by providing initial set-up values of pedal progression.
3. Candidates were found to be insensitive to small changes in progression.
4. Results from the eye-test appraisal indicate that drivers considered subjectively to be more aggressive in nature preferred a lower IIP. This indicates that they prefer and or require more control over the available power.

The formal statistical analysis procedure used to identify a CBM has produced the following conclusions:

1. The identified CBM gave a 95 per cent linear correlation between the 'ideal' progression and the resulting model.
2. Using many MRVs in the CBM *will* result in a better fitting model, but the overall statistical significance would be reduced.
3. Preliminary implementation of the model on a vehicle in real time demonstrates that the throttle progression adapts appropriately towards IIP, thereby matching the vehicle performance feel to driver expectations.

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APPENDIX

75th percentile Q_3

Percentiles are a measure of the distribution of the data. They focus on the central proportion of the data excluding the influence of outliers. The position of the upper quartile Q_3 is expressed as

$$Q_{3\text{POSN}} = \frac{3(n+1)}{4} \quad (13)$$

where n is the number of data points being sampled [5]. The Q_3 used is a rolling range parameter, being defined over a period of time. This lowers the variability and builds a true long-term model of the driver. The variability reductions compensate for ineffectual data such as that recorded while stationary at junctions, where both pedal position and vehicle speed are zero. The method used for calculating Q_3 would require the storage and sorting of an entire data set, which is inherently processor intensive and thus incapable of being executed in real time. The 'box' method is computationally much more efficient, allowing Q_3 to be found from a large data set which is continuously updated. Each 'box' is defined as a subdivision of the full range; thus

$$b_0 = X_{\text{MIN}} : X_{\text{MIN}} + (k+1)$$

$$b_1 = X_{\text{MIN}} + (k+0.01) : X_{\text{MIN}} + (k+1)$$

⋮

$$b_k = X_{\text{MIN}} + (k+0.01) : X_{\text{MAX}}$$

where

X_{MIN} = lower limit of range

X_{MAX} = upper limit of range

k = number of subdivisions

b = subdivision of range

Each new data sample recorded is rounded up to its nearest integer and placed in its corresponding box. The 'first' data point from the stored range is then removed from the sample, allowing the range to move in time. The number of counts is recorded for each box, and the position of Q_3 is calculated thus:

$$Q_{3\text{POSN}} = 3 \left(\sum_{i=k_{\text{LO}}}^{i=k_{\text{HI}}} x_i + 1 \right) / 4 \quad (14)$$

Q_3 is therefore the integer value of the box that contains $Q_{3\text{POSN}}$:

$$Q_3 = b_k(x_{Q_{3\text{POSN}}}) \quad (15)$$

The accuracy of the returned Q_3 is $-0.99 + 0.0$ units of

the appropriate sampled variable. The use of these slowly varying parameters gives a baseline for the adaptation process to work from. Using a static Q_3 would cause a delay the same length of time to that over which the

percentile is taken. This means that the adaptation process would always be adapting to how you have been driving and not how you are driving. This cannot be avoided, but its effects can be minimized.