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Publication Date

1998-08-01

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Evaluation of Work Crew and Highway Hazard Conspicuity

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**California PATH Working Paper
UCB-ITS-PWP-98-14**

This work was performed as part of the California PATH Program of the University of California, in cooperation with the State of California Business, Transportation, and Housing Agency, Department of Transportation; and the United States Department Transportation, Federal Highway Administration.

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Report for MOU 284

August 1998

ISSN 1055-1417

MOU 284 Final Report
Evaluation of Work Crew and Highway Hazard Conspicuity

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Abstract. The work reported here quantitatively addresses conspicuity of highway features, and in Caltrans work zones -- from the perspective of driver detection, and to some extent, driver decision making. It was initially focused on acquiring and operating on a computational visual signature analysis tool, but it evolved into evaluating the detection process, then selecting and exercising human perception-acquisition models suitable for relatively quick running and larger scale microsimulations to evaluate system effectiveness of “pre-AHS” driver-assist systems. This process and especially the recommended Bailey-Rand Contrast Model is described, and an detection example of a driver-assist collision avoidance model is provided.

Key Words. Conspicuity, Perception, Visual Performance, Human Vision, Microsimulation, Vigilance, Pre-attentive, Pre-cognitive, Contrast Model, Work Zones

Executive Summary. Work under this MOU was originally slated to employ a state-of-the-art visual signature analysis tool as a means to measure and improve conspicuity of human and roadway hazards on California highways. It was believed – and is still believed – that this tool could serve as a powerful, cost-effective and semi-automated method of “virtual prototyping” in which drivers’ perception of increased conspicuousness could be gauged. Notional designs and configurations could be simulated with very little investment, under different geometries, color/illumination combinations and ambient lighting conditions. The “best” design which optimizes some combination of cost-effectiveness and safety could then be confidently built and implemented.

Due to other PATH research needs, and availability of the computational vision tool, the work evolved into evaluating the detection process, then selecting and exercising human perception-acquisition models suitable for relatively quick running and larger scale SmartAHS microsimulations to evaluate system effectiveness of “pre-AHS” driver-assist systems. Because the SmartAHS-based work was aimed at assessing the safety of driver-assist devices, the work conducted in this MOU focused on models appropriate for that microsimulation, particularly as it fit into the *perception-decision making-control* hierarchy.

Two elements of perception were considered in this study human vision- and cognition-based detection models: *acquisition* (defined for here as proximal obstacle or vehicle detection probability P_d at range x) and *tracking* (defined for here as deceleration x' relative to the driver). In *acquisition*, progressively higher fidelity models in human vision-based target acquisition were shown, with positive and negative aspects described. The work began with the Bailey-Rand (BR) Contrast Model, then progressed to the Doll-Schmieder (DS) Model, and ended with the originally-proposed focus of work, the National Automotive Center-Visual Performance Model (VPM). These models are shown to sequentially yield higher confidence results in the analysis of more specific

driver-assist or work zone implementations and scenarios. In *tracking*, the work here is contained to a mathematical model describing longitudinal time to collision-based perception.

Of the three perception-acquisition models investigated – the Bailey Rand (BR) Contrast Model, the Doll-Schmieder Model and Visual Performance Model – the BR model is determined to be the “best” for short-term application into the SmartAHS microsimulation, due to a combination of believability and its low computational complexity. However, a logical progression and continued checking of computational complexity of salient aspects of the other listed candidate models is recommended in a carefully constructed longer term program to gradually build up the human vision aspects of SmartAHS. Additionally, incorporation of perception-tracking models is recommended, starting first with the already-explored longitudinal component and progressing to yet-to-be-explored lateral tracking.

Human vision models are applicable to the SmartAHS microsimulation mainly because of the impending driver-assist research needs. To illustrate how these models could be used, a collision avoidance case was illustrated. In that case, the need to supplement human detection with driver-assist detection technologies in inclement weather was highlighted. To more fully explore this and the potential ramifications of weather and configuration on Caltrans work zone conspicuity, especially in the context of the originally planned scope of this MOU 284, further elaboration on an probably not-for-SmartAHS tool – the Visual Performance Model – is suggested. This is precisely the focus of the follow-on MOU 328.

1.0 Introduction

This report is organized as follows: Section 1 (Introduction) contrasts the original and modified objectives of the project. Section 2 sets the overarching human driver model context, in which the current work fits. Section 3 of this report will show candidate perception-acquisition models for the SmartAHS microsimulation, and finally, Section 4 will provide an example of how the “best” model – defined as a combination of believability and quick-running – is used in a relevant driver-assist example.

Work under this MOU was originally slated to employ a state-of-the-art visual signature analysis tool as a means to measure and improve conspicuity of human and roadway hazards on California highways. It was believed – and is still believed – that this tool could serve as a powerful, cost-effective and semi-automated method of “virtual prototyping” in which drivers’ perception of increased conspicuousness could be gauged. Notional designs and configurations could be simulated with very little investment, under different geometries, color/illumination combinations and ambient lighting conditions. The “best” design which optimizes some combination of cost-effectiveness and safety could then be confidently built and implemented.

Three conspicuity subtopics were to be addressed:

1. Caltrans work zones;
2. highway configuration hazards (e.g., a high curvature off-ramp); and
3. roadway obstacles in a human-augmented Automated Highway Systems (AHS).

The end-product of the first two subtopics was to be a suite of recommended sign placement, color and configuration changes, and a concomitant quantification of the increased detectivity of these changes. The end-product of the third subtopic will be an assessment of human visual system capabilities and the degree of augmentation that may be required with driver displays to increase detectivity to AHS design thresholds.

As the project proceeded, however, three influencing events modified the work product:

Parallel research efforts were aimed at *driver-assist* “safety services”, which are presumably antecedent and certainly shorter-term in focus than AHS¹:

1. Emergence of the PATH SmartAHS effort, which is partially sponsored by Caltrans under MOU 258, and also the National Automated Highway Systems Consortium (NAHSC).
2. The SmartAHS microsimulation is being adapted to accommodate human driver models in order to expand its utility beyond full automation; the objective is to include this functionality to assess safety of driver-assist approaches. This requires input from MOU 284 work, namely credible, quick-running human vision models.
3. Difficulty in acquiring the genesis behind the project: a tool developed by the U.S. Army Tank-Automotive Research, Development and Engineering Center (TARDEC) and applied by the TARDEC National Automotive Center (NAC) and the General Motors Research and Development and Safety and Restraint Centers to detect taillight conspicuity. This tool, the NAC Visual Performance Model (VPM), was to be adapted for highway drivers and its use constituted the main thrust of the original project plan. The original legal vehicle to use this tool was to be a pre-arranged Cooperative Research and Development Agreement (CRADA) between PATH and TARDEC, but in time-consuming deliberations, TARDEC CRADA administrators determined not to go that route. Finally, toward the end of 1997, the VPM was supplied to PATH – too late to do substantial work in the planned area. However, due to reasons 1 and 2 above, ***under this MOU, significant research was accomplished in investigating visual perception models for use in driver-assist microsimulations and analyses.***

The original topics² are now essentially intact and to be addressed in the 97-98 MOU 328. Although they do not fulfill the currently-addressed need for quick running and

¹ Examples abound: in the U.S., the redirection of work conducted under the auspices of the NAHSC toward goals and objectives of the emerging US DOT Intelligent Vehicle Initiative; in Europe, analyses sponsored by the Dutch DOT to examine the effects of wide-scale market penetration of Adaptive Cruise Control (ACC) on traffic flow [1] and work conducted by Benz [2] to evaluate driver-assist aspects of the European Union CHAUFFER Project; in Japan, the focus on AHS-i (information) and AHS-c (control) rather than AHS-a (full automation) of the Advanced Cruise-Assist Highway System Research Association (AHSRA), a move which was probably strongly influenced by the Ministry of Construction.

² For reference, the following eight tasks comprised the original MOU 284 work plan:

Task 1. Acquire, evaluate and if necessary, customize and modify the VPM.

Task 2. Work with highway design, safety and operations practitioners to develop nominal configurations (i.e., scenarios) for all three research subtopics

Task 3. Develop image sets (photographs and post-photographic rendering, when necessary) of nominal configurations.

Task 4. Work with highway design, safety and operations practitioners to develop several notionally improved configuration variants.

Task 5. Assess relative improvement in conspicuity of different configurations by applying TVM.

believable human driver model inputs, they do fully address the original goals of the project, focusing in particular on an accurate (albeit computationally-intensive) methodology to assess relative improvements in conspicuity enhancements for Caltrans work zones.

2.0 Framework to Describe Human Driving

Several taxonomies have been developed describe the sequence of “normal”, i.e., non-emergency, driving actions: *perception-decision making-control*, *navigation-guidance-control*, and the *3T* architecture. The *perception-decision making-control* triplet was derived to describe localized, near-term driver actions [3]. The *navigation-guidance-control* conceptual framework was developed to bridge higher level goal-setting or navigation activities with near-term driver or *control* actions via monitoring, or *guidance* [4]. The *3T* architecture navigates an automaton via a succession of micro-level skills, then progressing to tactical and strategic levels [5].

Because the SmartAHS application is aimed at assessing the safety of driver-assist devices, the work conducted in this MOU focused on the local (or borrowing from the *3T* lexicon, tactical) layer, bypassing the guidance or strategic levels. The model structure that the MOU 284 work was fit is therefore the *perception-decision making-control* hierarchy.

As an important note, for simplicity an alerted driver is assumed – one who is already vigilant, attentive and monitoring. These necessary conditions for full cognition are

Task 6. Initiate assessing absolute “best” configurations by calibrating for absolute detection; design human jury verification and validation experiments in collaboration with researchers at TARDEC NAC and General Motors. (The experiments are to be conducted by these organizations as part of their separate and parallel experimental program.)

Task 7. Reiterate Tasks 2 - 6 to optimize or reassess configurations.

Task 8. Deliver final recommendations and final report.

generally described in a wide body of supervisory control literature [6,7,8]. The specifics of objectively modeling these precursors to perception is a complex undertaking [9], and one that is deferred in the current project. A simplifying advantage of not addressing this in the MOU is that by considering only an already-alerted driver, complicated issues in warning and human machine interface design are sidestepped; the focus is clearly on driver reactions, and on responses to exogenous disturbances from outside the vehicle.

3.0 Perception Models

Two elements of perception should be considered in human vision- and cognition-based detection models: *acquisition* (defined for our purposes as proximal obstacle or vehicle detection probability P_d at range x) and *tracking* (defined for our purposes as deceleration x' relative to the driver).

3.1 Acquisition Models. Progressively higher fidelity models in human vision-based target acquisition are shown with positive and negative aspects described. The description begins with the Bailey-Rand (BR) Contrast Model, then progresses to the Doll-Schmieder (DS) Model, and ends with the NAC-Visual Performance Model (VPM). These models will sequentially yield higher confidence results in the analysis of more specific driver-assist or work zone implementations and scenarios.

3.1.1 Bailey-Rand Contrast and Similar Models. The BR model incorporates, in a compact manner, the first-order effects of luminance contrast. To do so, it assumes that targets are static and can be represented by circles with varying contrasts to an appreciably uniform (and therefore uncluttered) background [10,11]. Given these simplifications, the prediction of the detection probability as a function of range x , $P_d(x)$, is relatively straightforward:

$$P_d = \frac{1}{2} \pm \frac{1}{2} \left\{ 1 - \exp \left[-4.2 \left(\frac{C_R}{C_T} - 1 \right)^2 \right] \right\}^{\frac{1}{2}}$$

“+” when $\frac{C_R}{C_T} \geq 1$
 “-” when $\frac{C_R}{C_T} < 1$,

(1)

where

$$C_T = 10^{-2} 10^{\left[\frac{1}{\log(3440(D/x)+0.5)} \right]},$$
(2)

and

$$C_R = \frac{C_0}{1 + SGR \left[\exp \left(3.912 \frac{x}{V} \right) - 1 \right]},$$
(3)

where C_T is the human detection threshold, and D/x is an angular resolution term which may be expressed in terms of line pairs/target (when viewed through a vision enhancement device), cycles/mrad, or some other appropriate measure of spatial frequency. Also, C_R is the apparent contrast and is expressed as a function of C_0 , the physical target contrast with the local surround; SGR is the sky-to-ground luminance ratio; the parameter D is the diameter of the equivalent area target circle; and x is the detection range.

The BR model also includes a target visibility V factor, or the maximum range to a target with $C_R = 1$, where C_R is diminished no more than 2%. Atmospheric phenomenology – specifically, the magnitude of weather obscuration affecting P_d – can be represented in V by pairing it with a Beer-Lambert or Koschmeider’s Law multiplier:

$$T(\lambda) = e^{-ax} \quad (4)$$

where $T(\lambda)$ is the transmittance and a is the precipitation volume extinction coefficient (km^{-1}). Expressions for a are available in the form br^c and values for b and c for a variety of natural and manmade obscurants, and also as a function of density, e.g., rain rate [12,13].

Limitations of the BR model primarily include the aforementioned assumption of static, circular targets. (Some targets such as stalled vehicles and stationary objects are certainly static, but the driver's vehicle is normally moving, nominally at 30 m/s or 10 m during the 1/3 s glimpse.) Moreover, the surround is not clutter-free, and scenes have considerably more spatial, spectral (such as color) and temporal features that contribute toward target discrimination, e.g., transient glare. These assumptions may be less far-fetched under certain constrained scenarios such as with a limited search within a rural highway and under relatively high but diffuse luminance. However, they have been successfully applied in DoD applications [11], on non-circular targets and on natural backgrounds with considerably more clutter than many highway scenes. ***For this reason, the computationally-simple BR model can be confidently used in SmartAHS under carefully designed scenarios.***

In the related and follow-on work in MOU 258 to adapt the BR model into SmartAHS, the initial plan is to improve BR formulation by incorporating an explicit driver search model. Because of its empirical foundation, we will maintain the independent 1/3 s BR glimpses. Head dwell and gaze abduction behavior measurements have been conducted for driving [14] and at intersections [15], but there are very few field experiments on which to build driver visual search models [16]. For the most probable near- to mid-term driver-assist focus at PATH on forward driving on limited access highways, work from [14] is

expected to be incorporated; in it, the driver will be assumed to direct her alerted search to the lane directly ahead.

Finally, it should be noted that the BR model differs from the Visibility Index and Visibility Index/Fog (VI/FOG) models used in the NHTSA-sponsored Perception-Decision-Response framework constructed to assess causes of reduced visibility crashes [20], in that the BR model more rigorously defines meteorological parameters affecting detectability. The VI/FOG models, however, take glare from artificial illumination into consideration, including streetlights. An improvement to the psychophysics embedded within the VI/FOG models is represented by the PCDETECT model, which takes into account driver age and glare. All three competing models (BR, VI/FOG, PCDETECT) are based on data from the classical Blackwell experiments, which relate differences in visual contrast over a wide range of illumination conditions [17,18,19,20]. In these experiments, targets are circular, the background is uniform, and the target-to-background discriminant is luminance (i.e., gray scale) contrast. As these assumptions exist within the other models, the common foundation makes use of any of the three similar classes of models almost equally valid. The BR model is preferred for adoption into SmartAHS because it can be compactly expressed in three equations (Eq. 1 - 3), and it is acknowledged outside the transportation safety community [11]. ***However, given time a resources, a more robust and higher fidelity representation of the human visual system is recommended to reduce systematic errors from the simplifying assumptions of the BR and like models.***

3.1.2 Doll-Schmieder and Related Models. The DS model overcomes clutter limitations and introduces a theoretical framework -- the Theory of Signal Detection (TSD) -- for detection decision-making [21]. This framework is implicit with Blackwell's relationships.

The use of TSD puts the DS model into class of acquisition models commonly used for in sensor processing. In this class of models, the detection function can generally be written as:

$$P_d = a_e r_d f_{sensor} \left(P_a^f, p_{md}, SCR, p_n, a_o, \frac{p_o(x)}{p_b(x)} \right) \quad (5)$$

where a_e is the atmospheric extinction, and the sensor processing function f_{sensor} is written in terms of a combination of obstacle-descriptive parameters (area a_o , range x , target signature distribution $p_o(x)$), background-descriptive parameters (background signature spatial distribution $p_b(x)$), and sensor and sensor processing parameters (sensor noise distribution p_n , false alarm probability P_{fa} , missed detection probability p_{md} , detection range r_d , signal-to-clutter threshold design point SCR).

Each sensing system possesses unique detection decision criteria which comprise the factors within f_{sensor} , and as such f_{sensor} has a wide design space. For example, a FCA radar designer will likely specify what is termed a Neyman-Pearson or likelihood ratio receiver [22], where P_{fa} and p_{md} are stochastic distributions. The compromise or design point between these distributions can be specified by first determining the likelihood ratio SCR/p_n [22]. When we consider that $P_{fa} = f(SCR/p_n)$ and then f is highly dependent on the specific radar processing design. In addition, *a priori* knowledge of the range of target and background signature characteristics is necessary in determining SCR .

For military vehicles in rural clutter, Doll and Schmieder have recognized that the human vision system is f_{sensor} , and they have predicted P_{fa} as a function of clutter, resolution and range [23]. Their Neyman-Pearson receiver is an application of TSD decision-making ,

where the target and clutter are considered as Gaussian ogives with a mean of 0 and variance of 1. Hence,

$$P_d(SCR, C_T) = 2^{-[1-h(SCR)-C_T]^3}, \text{ and} \quad (6)$$

$$P_{fa}(C_T) = 2^{-(1+hC_T)^3}. \quad (7)$$

A parametric fit of observer data is required to fit a linear relationship between the h and $SCR - C_T$ values. Doll and Schmieder have done so with military vehicles in rural clutter and are thus able to predict false alarm probabilities, P_{fa} , as a function of clutter, resolution and range.

To make the application of TSD in modeling detectivity by humans complete, the models must be populated with specific background imagery, then human jury tests to determine ROC's must be conducted. Hence, to make this model applicable for highways, appropriate vehicle, obstacle and highway scene data must be gathered and fit. The data set could be large, as variations such as the diurnal cycle, different highway topologies and obstacle types must be considered; however, given a contained and very specific scenario, a reasonable data set with a high degree of realistic visual cues could be collected, i.e., glint, glare and other spatially or temporally unique features.

Although the DS model overcomes the simplified target and background assumptions of the BR model, it still applies to stationary objects. Additionally, vehicle motion and the decision whether the detected object is an obstacle are still not addressed by this model.

3.1.3 National Automotive Center - Visual Performance Model (VPM). An early vision model to detect highway obstacles can be applied to overcome the aforementioned deficiencies. The VPM once such early vision model, combining precepts of preattentive

vision and human reasoning to model the human visual/detection system and reconciles recent theories of post-receptor chromatic-achromatic independence, visual multiplexing and texture perception, then performs a TSD post-processing to simulate the complex sequence of events which comprises what has been termed the psychophysical zone theory of human detection [24,25]. In essence, the VPM introduces effects of color and motion with mathematical representations of the early vision process from the receipt of photons on the retina through response by the photoreceptive fields, and concluding with TSD for the target detection decision. The VPM combines aspects of preattentive vision and human reasoning to model the human visual/detection system.

As with the human, VPM produces sequential channels for color (obtained by dividing the image into color-opponent channels), motion (obtained by temporal filtering), spatial frequency (obtained by transforming images into two-dimensional frequency space scenes) and orientation (obtained by performing horizontal and vertical filtering). The model produces a signal-to-noise ratio for each channel, then summed over all channels to essentially produce a *ROC*, and from TSD, P_d and P_{fa} [23].

The VPM is the product of a multi-year, multi-million dollar investment by the Army Laboratory Command, Weapons Technology Directorate (WTD), working with TARDEC. A large-scale investment is currently underway by TARDEC, the U.S. Army Human Performance Laboratory, and the U.S. Army Combat Systems and Test Activity to calibrate, validate and verify the code. As stated in the introduction, the VPM is now available at PATH, to be used in MOU 328.

Mathematical models such as VPM have only recently been formulated to emulate the human early vision process [24,25]. The VPM is available to the authors, but there are other similar models such as Visually-Guided Threats (VGT) model [26]. Both the VPM

and VGT models analyze characteristics such as motion, color, spatial frequency and orientation by decomposing visually multiplexed color-opponent images.

Human vision can be regarded as a sequence of preattentive and cognitive functions. The series of preattentive human vision functions, as modeled by VPM, is approximated by [25]:

- digitizing color video image or independent frames to represent composite macular/peripheral scene images, within the gamut limitations of capturing “true color”;
- temporally filtering these images into three component images: sustained (lowpass), transient (mid-frequency bandpass) and highly transient (high-frequency bandpass);
- separating color and luminance into five channels (black-white, or luminance only, for each temporal segment, and -- because human color-opponent channels are insensitive to transients -- red-green and yellow-blue channels for the lowpass segment only);
- transforming separated color-opponent and luminance images into nine pseudo-images in two dimensional frequency space, with center frequencies spaced at one octave intervals; and
- performing horizontal and vertical orientation filtering on each image.

The resultant 90 images (5 color-opponent images x 9 frequency space images x 2 image orientations) are disaggregated by temporal, luminance, color-opponent, spatial and orientation characteristics. These can be directly viewed with VPM, then analyzed in a conspicuousness design sense for spatial energies (for likely detection features) and interchannel covariance (for phase information and, therefore, interrelated edge-detection design attributes).

However, to complete the serial preattentive-cognitive model of human detection, an intermediate, translation step must be performed by determining the “visual information metric” to combine spatial energies over pre-selected regions or over the overall image scene; this metric is essentially a chi-square statistic to determine signal and clutter contributions [27].

From this, cognitive functions are modeled by [27]:

- implementing a search and detection scheme, to include probabilities of incurring single- and multiple-saccade, or glimpses, for human scan behavior; and finally,
- processing the data using TSD to derive ROC curves to relate P_d and P_{fa} and derive t_{od} .

The visual multiplexing of color-opponent channels during the preattentive vision sequence occurs through a set of spatio-temporal decoding rules, and are dependent on a set of weighted sensitivity functions. These functions are empirically adjusted and may have to be further changed for use in the proposed highway application. In addition, the visual search module contained within VPM may have to be adapted for human-cognitive behavior during highway driving via some logical *a priori* assumptions of the typical driver search. The VPM search model is based on human visual search in cluttered combat backgrounds; however, elements of this may not be extendible to highway driving without these adjustments.

3.2 Tracking Model. In light of the PATH near term objective of determining the efficacy of longitudinal control and warning, the focus on tracking models has been limited to longitudinal acceleration only. To be complete, tracking of objects moving laterally across the field of view (e.g., deer on the roadway, or cars crossing at an intersection) would also have to be addressed. Such a model would be complex, and look up tables of empirically derived eye tracking data such as from [14] might be the most appropriate means to approach the problem. At the present time, and due to these complexities, a lateral tracking model is not being considered for SmartAHS.

In considering longitudinal tracking, work in estimated time to collision (TTC) was investigated. The TTC estimates are obtained from empirical studies of variations from the population norm. This measure is a standard input to highway design standards

[28]. In recent years, however, the question of how drivers gauge TTC has arisen. It is now known that the human visual system is sensitive to the looming angular target size ω and its rate of increase (or decrease) $d\omega/dt$, but it is not certain whether the driver is directly sensitive to $\omega/(d\omega/dt)$, or equivalently, TTC [28,29]. Whatever the exact mechanism, at distances defined at $d\omega/dt < 0.003$ rad/s, drivers are unable to discern differences in relative speed; at values above this threshold, drivers scale perceived speed in a practically linear relationship to ω , at discrete just-noticeable increments of $d\omega/dt = 0.12$ [31]. This can be expressed as [30,31]:

$$v = \frac{x^2 \omega}{d} \quad (8)$$

where v is the perceived relative velocity between the driver and the forward vehicle or obstacle, x is the distance between the vehicles, and d is the forward vehicle or obstacle diameter. To be consistent with [31] we will implement Eq. 6 in SmartAHS at 1/3 s glimpses (to be consistent with the BR assumption), with perceived v subject to a $d\omega/dt > 0.003$ rad/s threshold and changing only at $d\omega/dt = 0.12$ increments.

4.0 Driver-Assist Application of the BR Contrast Model

4.1 Background. An elemental factor in analyzing the requirements for and benefits from a longitudinal driver-assist service is the probability of proximate obstacle or vehicle detection. The detection probability may be an important factor in assessing crash probabilities, along with probability distribution functions of driver vigilance and attentiveness. (The aforementioned descriptive “longitudinal driver assist” service is conventionally categorized as a Collision Avoidance System, or CAS. There are two types of CAS: a forward collision warning, or FCW; or a forward collision avoidance, or FCA, system depending on whether its intervention is in driver warning or takeover of control. In the example shown below the “longitudinal driver assist” service will be

dubbed CAS, and the particular problem will be termed the Lead Vehicle Note Moving, or LVNM, problem.)

Accurate values for human detection performance would immensely aid in the estimation of CAS worthiness, but given the difficulty of this, we believe that an understanding of sensitivities of these is a sufficient and reasonable starting point; that is, the “human element” should be understood at least to the extent that it and any controlling parameters can be specified along with tolerance limits. This allows both a basis for comparison (i.e., without CAS vs. with various CAS types) and a methodology to design an appropriate set of experiments to verify inputs and validate results. With specific regard to proximate vehicle detection, even if detection probabilities turn out to be the same with and without collision warning, any level of understanding these probabilities and their sensitivities (e.g., weather and atmospheric extinction, conditional vigilance) will aid in:

- understanding the contribution of vision to crash causes;
- in defining sensor specifications for the requisite vision enhancement; and finally,
- in more accurately assessing the benefits of implementing crash countermeasures.

This view is at least partially shared in the National Highway and Transportation Safety Administration (NHTSA)-sponsored assessment of reduced visibility crash causes with the development of a Perception-Decision-Response (PDR) framework [32].

The application of the BR model to CAS highlights the importance of understanding and modeling target, background and weather characteristics toward proximate vehicle detection. It serves as an illustration on how human sensing parameters can be applied to highlight input sensitivities and particular data needs to help focus subsequent experimental efforts. This example also illustrates the effects of atmospheric conditions.

4.2 Problem Formulation. The LVNM forward collision warning sensing system should yield the basic outputs of distance to the obstacle x_{od} and detection and response time t_{od} , which would in turn be translated to the net longitudinal stopping distance d via

$$d = x_{od} - t_{od}v, \quad (9)$$

where d is the net longitudinal stopping distance and v is the average vehicle speed during the target acquisition.

However, d is also a function of many detection-specific parameters which must be made explicit. These parameters are universal, as they can, in a unified manner, describe a variety of obstacle detection sensing systems, including human detection.

This detection function can generally be written as:

$$P_d = a_e x_{od} f_{sensor} \left(SCR, p_n, a_o, \frac{p_o(x)}{p_b(x)} \right) \quad (10)$$

atmospheric extinction a_e ; obstacle-descriptive parameters (area a_o , range x , target signature distribution $p_o(x)$); background-descriptive parameters (background signature spatial distribution $p_b(x)$); and sensor and sensor processing parameters (sensor noise distribution p_n , false alarm probability p_{fa} , signal to clutter threshold design point SCR).

4.3 Use of the Bailey-Rand Contrast Model. In this example, the BR model is applied to “get in the ballpark” in determining P_d and also to understand sensitivities to input parameters. The example utilizes the modeled first-order effects of luminance contrast, plus the representation of atmospheric phenomenology.

In abstracting the LVNM target for the BR model, the LVNM target must be recognized to be static (and also therefore not subject to any companion tracking model such as described in Section 3.2). However, it is certainly not circular, nor the surround to clutter-free; moreover, considerably more spatial, spectral and temporal description is necessary to capture the early vision process. The BR model is a first-principles method to “get in the ballpark”. As a note, although the clutter-free background assumption is not the case with most roadways, it can be envisioned to be true in certain constrained-area surrounds. (The highway scene, sans other vehicles, certainly has less local clutter than many natural backgrounds.) Once more, this assumption is made to “get in the ballpark”.

Note also that there is no explicit driver search model in the BR formulation; rather, each 1/3 s BR glimpse is assumed to be independent. Various investigators have debated the independent glimpse assumption for the battlefield surveillance task [10,25], but aside from investigating overt head dwell and gaze abduction behavior at intersections, there are very few field experiments on which to build driver visual search models [14]. We expect that with the presence of a LVNM collision warning signal, the driver will contain any alerted search within the lane directly ahead; however, this is not necessarily the search pattern for most normal driving.

In applying the BR model to the LVNM case, we substitute the following parameter values into Eq. 1:

In determining C_T :

$$D = 2.26 \text{ m (4 m}^2 \text{ target)}$$

In determining C_R :

$$C_o = \frac{L_o - L_b}{L_b} = \frac{R_o - R_b}{R_b} = \frac{0.5 - 0.15}{0.15} = 2.3 \quad (11)$$

The L_o and L_b quantities are target and background luminance, respectively. Given the same insolation, they equate to first order to R_o and R_b , the target and background reflectances. Substituting readily available values for R_o and R_b yields a value for C_o [11,12]

$SGR = 1.4$, a typical value for clear skies and desert conditions [11]. Values for desert floor reflectivity are near those for asphalt reflectivity [12], and the environment is nearly clutter-free, similar to unobscured road surfaces. Variations due to SGR are typically due to different sky conditions (e.g., clear vs. diffuse) and terrestrial surface reflectivities (e.g., snow vs. desert vs. forest canopy). The range of SGR values is 0.2 (clear sky, snow surface), to 25 (diffuse sky, forest canopy surface).

Using the BR input values for the ranges considered ($x = 90 - 160$ m), $C_T(90 \text{ m}) = 0.033$, and $C_R/C_T > 1$. For a singular $1/3$ s glimpse, $P_d = 1.0$ at a typical $V = 10,000$ m [9]. This confirms intuition: a visually unimpaired and alerted human performs well in an unobscured direct line-of-sight detection task over relatively short ranges.

It is more interesting to study the effect of x/V , the ratio of detection distance to visibility, on P_d as it allows us to determine the effects of weather obscuration. This is because V corresponds to the atmospheric extinction due to environmental obscurants as fog and rain (along with SGR).

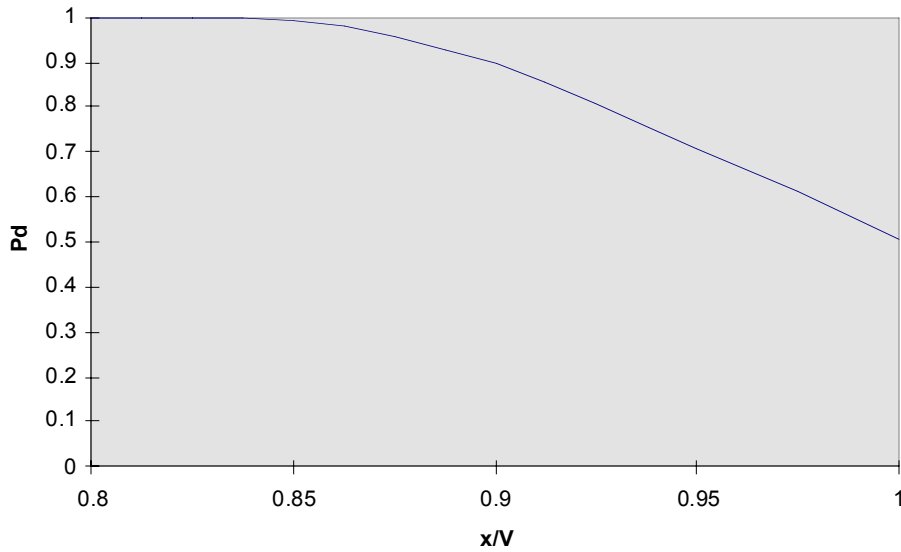


Figure 1. BR-Derived Detection Probabilities Expressed as a Function of the Ratio of Detection Distance to Visibility.

In Figure 1, the x/V parameter of the BR model was varied at a fixed range $x = 90$ m, and a greatly reduced V (or equivalently, an increased x/V up to $x/V = 1$) was shown to result in considerable degradation in human detection performance. ***It can be concluded that the human P_d will diminish rapidly under extremely obscured or inclement conditions -- and that some obscurant penetrating system as millimeter wave or laser radar is needed as a vision enhancement under these conditions.***

The rain rate required to elicit this value of V can be determined by substituting empirical rain rate-extinction relationships into the Beer-Lambert or Koschmeider's Law previously shown in Eq. 4. The empirical expression to determine a under moderate/widespread rain conditions is:

$$a = 0.36r^{0.63} \quad (12)$$

where r is the rain rate expressed in mm/h [11].

With $T(\lambda) = 0.98$, $r = 2.9$ mm/h. Interestingly, with $x/V = 1$ (corresponding to $V = 1$ and $P_d = 0.51$), $r = 2.1$ mm/h. Both these rain rates fall within the definition for the common condition of moderate/widespread rain [9,10]. Hence, for the analyzed LVNM case, P_d 's can begin to fall off dramatically with small variations in even moderately inclement weather.

This result points to the potentially frequent need for human vision augmentation in a LVNM crash avoidance system. Moreover, the augmenting device should be some type of a rain-penetrating sensing system. The results also begin to clarify the value of the human detection probability component in a LVNM crash avoidance benefits assessment. It follows that better human vision models -- which exist and can be adapted within the benefits assessment framework -- would yield higher confidence answers.

5.0 Conclusions

Of the three perception-acquisition models investigated – the Bailey Rand Contrast Model, the Doll-Schmieder Model and Visual Performance Model – the BR model is the “best” for short-term application into SmartAHS due to a combination of believability and its low computational complexity. However, a logical progression and continued checking of computational complexity of salient aspects of the other listed candidate models is recommended in a carefully constructed longer term program to gradually build up the human vision aspects of SmartAHS. Additionally, incorporation of perception-tracking models is recommended, starting first with the already-explored longitudinal component and progressing to yet-to-be-explored lateral tracking.

Human vision models are applicable to SmartAHS only because of the impending driver-assist uses. One such use in CAS was illustrated, and the need to supplement human detection with driver-assist detection technologies in inclement weather was highlighted. To more fully explore this and the potential ramifications of weather and configuration on Caltrans work zone conspicuity, especially in the context of the originally planned scope of this MOU 284, further elaboration on an probably not-for-SmartAHS tool – the Visual Performance Model – is suggested. This is precisely the focus of the follow-on MOU 328.

6.0 References

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7.0 Glossary

abductive: the angular range that eyeses move during visual search, measured from the median axis of the body

achromatic: not related to color (e.g., black-white images)

chromatic-achromatic independence: referring to the theory that black-white and color-opponent vision channels separately constitute human detection channels

cognitive: refers to tasks of which the human is aware or passes judgement
color gamut: the full representation of color space allowable by the medium
color-opponent: red-green and blue-yellow components of the theory of chromatic-achromatic independence
luminance: a measure of light in the visual spectrum, synonymous with “photometric brightness” [lumen per steradian and square meter, or nit]
macular: relates to high acuity vision in the most sensitive part of the human retina
photoabsorption: absorption of photons (light) by the retina
preattentive: refers to tasks of which the human is unaware
psychophysical: relating physical parameters (such as various visual stimuli) to mental processing (such as detection cognition)
saccade: quick, smooth eye movement (such as a glimpse)
visual multiplexing: the fusion of spatio-temporal neural processes