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Computing the probability of target detection in dynamic visual scenes containing clutter using fuzzy logic approach

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ABSTRACT

The probability of detection (Pd) of moving targets in visually cluttered scenes is computed using the Fuzzy Logic Approach (FLA). The FLA is presented by the authors as a robust method for the computation and prediction of the Pd of targets in cluttered scenes with sparse data. A limited data set of visual imagery has been used to model the relationships between several input parameters; the contrast, vehicle camouflage, range, aspect, width, and experimental Pd. The fuzzy and neuro-fuzzy models gave predicted Pd values that had 0.9 correlation to the experimental Pd's. The results obtained

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indicate the robustness of the fuzzy-based modeling techniques and the potential applicability of the FLA to those types of problems having to do with the modeling of aided or unaided detection of a signal (acoustic, electromagnetic) in any spectral regime.

1.0 INTRODUCTION

Typically the detection of moving targets by observers is of equal if not more importance than the detection of stationary targets. For the two classical ground warfare conditions, one side attacking the other or both sides moving and meeting in an engagement, evaluation of electronic systems that are to be used in target acquisition or to depend on target acquisition subsystems have to include a performance analysis against moving targets.

At the present time, the majority of target acquisition devices on the battlefield are man-in-the-loop. That is, a human operator or gunner interprets the image generated and displayed by the sensor and target acquisition system. Understanding the interaction between the human interpreting the images and the performance of the system is required for a complete evaluation of the systems and or modeling of the systems performance for target acquisition.

The target acquisition model currently used by the Army [1,2] predicts the probability of detection (Pd) as a function of Minimum Resolvable Contrast, (MRC) target size and contrast, and a target/background interaction parameter, N50. The parameter N50 (also known as the Johnson criteria), is defined to be the number of resolvable cycles necessary for 50% of the observer population to acquire the target.[3] In current practice, a single standard value of N50 is used for stationary targets and a different value of N50 is used for moving targets. The value of N50 for moving targets is assumed to be one half the value of N50 for stationary targets in a low clutter scene. This assumption is based on the qualitative observation that moving targets are easier to detect than stationary targets and are equivalent to detection of a stationary target with a uniform background. This assumption does not take into account either speed or direction of motion of the target with respect to the observer.

There is very little useful tactically realistic data on moving ground targets. By their nature, field experiments for moving targets are very difficult and expensive to design, instrument and conduct. Vision research data does exist, but realistic scenes involving moving ground vehicles are not used. The purpose of this experiment was to collect and analyze scientific and statistically significant data to gain insight into the factors that influence human observer detection of moving targets in realistic, natural backgrounds. Tactical field experiments have proven impractical and insufficient for generating sufficient data for model development and validation. Perception experiments in the laboratory setting, i.e. the TARDEC Visual Perception Laboratory in Warren, Michigan, using actual scenes displayed on a computer monitor provide a reasonable alternative and supplement to costly field trials.

Tactical realistic close combat primarily consists of field-of-regard (FOR) search; however, developing perception experiments either on the field or using field acquired tactical images is logistically and technically difficult and impractical. Search and target acquisition (STA) can be investigated separately. This experiment concentrated on the target acquisition of moving targets in clutter. In particular, this experiment was concerned with the foveal detection of stationary and moving targets in a controlled environment. By foveal detection, we mean detection of a target that was located (and known to be) in the center of the image.

2.0 MOVING TARGET TESTING METHODOLOGY

The perception testing was conducted using the Director MultiMedia for PC software. The subjects viewing distance was controlled so that the apparent target size was accurate for each target range. The approach used was to present visual stimuli containing a random presentation of four factors. The four factors of interest in this experiment were contrast, velocity, range, and background. As mentioned in the preceding pages, the factor of primary interest in this experiment was motion. In this initial study of the effect of motion on detection, it was not known a priori how the various factors in the stimuli set interacted to produce a detection event. For this reason, it was deemed appropriate to do a full factorial design with an ANOVA. [4].

The test involved a total of 23 subjects. The subjects were recruited by a market opinion company. All subjects had military experience of some kind, in either the active Army, the Reserves or the Guard. All subjects were between 20 and 45 years of age with normal vision or vision corrected to 20/20. Prior to the execution of each stimuli presentation the subjects were screened for vision abnormalities using a Snellen chart and Ishihara color plate book. The subjects were tested one-at-a-time, two per day, over a period of 3 weeks. Each subject received a half hour of orientation and training on the test equipment prior to the actual data collection. The test protocol presented a sequence of 500 dynamic stimuli to each subject. Targets were present in 90% of the 500 trials and 'no targets' were present in the other 10%. Each dynamic sequence was presented for 3 seconds. As soon as the subject decided whether or not a target was present, he pressed a response button, "YES" a target was there, or

"NO" there was no target. If the 3 seconds elapsed without a response, a "time out" was recorded, and the trial was treated as a "no target detected" response.

The stimuli data set was created from 35mm visual imagery taken during a field test exercise. This exercise was conducted in a desert environment. Five images with different clutter [5] and contrast [6] levels were selected. Each of the images were developed in three versions, stationary target, moving target, and no target. The stationery target was the original image. The moving targets were made by using a commercial software package to incrementally 'move' the target at a perpendicular direction to the observer's line-of-sight (LOS). For the no target image, the target was removed, and background was placed where the target had been. Fig. 1 is an example image from the data set showing the starting position of the vehicle.

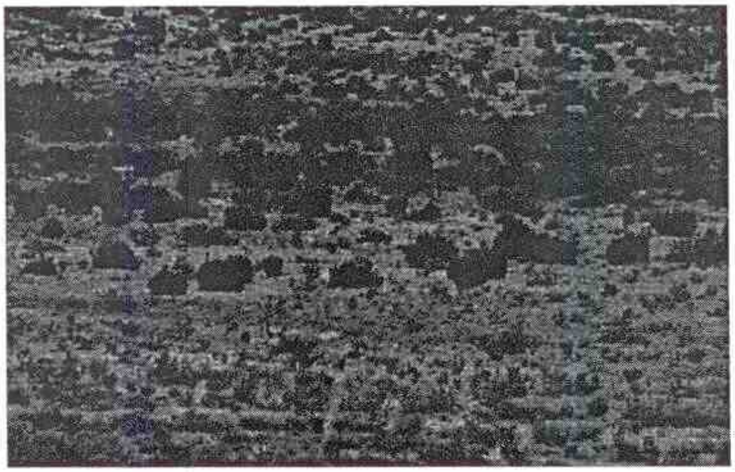

Fig. 1 Sample image used as stimuli

Commercial software was used to create the motion sequences. Three motion sequences were created corresponding to lateral ground speeds of 0, 5, and 20 kilometers per hour (kph). All motion began with the target in the center of the image, and lateral motion was from right to left. Once the baseline sequences were generated, the images were scaled to represent different ranges. The observer was seated 1.3 meters from a nominal 17 inch monitor and the target size was configured to represent ten simulated ranges: 1500 meters to 6000 meters in 500 meter increments. The software was also used to create stationary and motion sequences for targets with reduced contrast. The original image represented the high contrast target. The brightness level of the target was decreased to represent lower contrasts. This process was conducted twice, yielding three contrast levels for each image.

The computer monitor used for this perception test was a Panasonic PanaSync/Pro P17 display. The monitor was black and white level adjusted for the light level used in the experiment and then luminance data was collected for computation of the red, green and blue gamma values.

2.1 PERCEPTION LABORATORY FACILITIES

Fig. 2 shows a view of the main test area as viewed through the control room window. The whole facility consists of a 2500 square-foot area which can accommodate vehicles ranging in size up to the Bradley Infantry Fighting vehicle. This scene also shows a half-car mock-up that was used in a recent Cooperative Research and Development Agreement (CRDA) surrounded by three rear projection video screens which display the driver's front, left and right views of the intersection traffic. Fig. 3 shows a visual scene containing camouflaged targets located along a tree line as seen from the drivers position in a HMMWV. Visual perception experiments conducted from such scenes will allow U.S. Army researchers to study wide field of regard (FOR) search and target acquisition (STA) strategies for future low contrast vehicle signatures.

2.2 EXPERIMENTAL DESIGN

The general design used in this experiment was a full-factorial for 4 factors [4]. The factors and their interactions that were explored were: background (clutter level), target to background contrast, range and velocity. The levels of each factor are found in Table I. The experiment was performed by randomly selecting a treatment combination and then recording electronically an indication from the subject as to "YES" or "NO" that they saw a target. The "target" was defined to the subjects in advance as being a military target and the subjects were shown pictures of the vehicle and a training sequence that was similar to the actual test sequence. Because of the subject availability, 23 subjects were involved in the study, it was convenient to have each subject view all 500 scene combinations. Since humans differ in their ability to perceive targets embedded in natural backgrounds the subjects were used as blocks. The treatment combination was randomized. The experimental design was a 5 X 3 X 3 X 10 factorial experiment run in randomized complete block. [4]

TABLE I

FACTOR	SPECIFIC CONDITIONS	LEVEL NUMBER
Background (clutter level)	Five different visual scenes with military target	5
Contrast	Original and at 2 lower brightness settings	3
Velocity	Stationary, 5kph, 20kph	3
Simulated range	1500m...6000m at 500m increments	10
Subproduct		**450**
No-target images	10 simulated ranges x 5 images	50
Total		**500**

3.0 ANALYSIS

We performed an analysis of variance (ANOVA) to determine which of the factors and interactions had statistically significant linear effects on the probability of detection. We conducted a partition analysis to assess the effects of categorical variables and to examine potential non-linear effects and interactions. We also analyzed the false positive response data to test for possible biases in the experiment. At the present time, our analysis has been restricted to the detection response data . The results of the analysis indicate that ***all the main factors and all the second order interactions except for the contrast and velocity and contrast and range were significant at the 1 percent level***. The analysis of variance for this experiment is summarized in Table II.

Table II. Analysis of Variance

Source	Sum-of-Squares	Degrees of Freedom	Mean-Square	F-Ratio	P-value
BACKGROUND	144.474	4	36.118	212.953	0.000
CONTRAST	16.820	2	8.410	49.586	0.000
VELOCITY	86.154	2	43.077	253.979	0.000
RANGE	308.934	9	34.326	202.385	0.000
BLOCK	55.546	22	11.616	68.486	0.000
RANGE*VELOCITY	35.611	18	1.978	11.665	0.000
BACKGROUND*VELOCITY	11.044	8	1.380	8.139	0.000
BACKGROUND*CONTRAST	6.483	8	0.810	4.778	0.000
RANGE*BACKGROUND	36.615	36	1.017	5.997	0.000

3.1 METHOD TO COMPUTE Pd AND DPRIME

Classical signal detection theory [7] uses d' to predict single-glimpse probabilities of correct detections, or "hits" Pd, and false alarms Pfa. Pd and Pfa are determined from equations such as (1)

$$P_d = 1 - \Phi(k - d') \tag{1}$$

or, rearranging (1) above gives,

$$(k - d') = \Phi^{-1}(1 - P_d) \tag{2}$$

$$P_{fa} = 1 - \Phi(k) \tag{3}$$

or,

$$K = \Phi^{-1}(1 - P_{fa}) \tag{4}$$

Subtracting (4) from (2) gives dprime,

$$d' = \Phi^{-1}(1 - P_{fa}) - \Phi^{-1}(1 - P_d) \tag{5}$$

The inverse of the normal distribution function is given for $0 < Pd < 0.5$,

$$\begin{aligned} &k - d' = -t - \frac{(c0 + c1t + c2t^2)}{(1 + d1t + d2t^2 + d3t^3) + \varepsilon(p)} \\ &where, \\ &t = \sqrt{\ln\left(\frac{1}{P_d^{\,2}}\right)} \end{aligned} \tag{6}$$

and for $0.5 < Pd < 1$

$$\begin{aligned} &k - d' = -t + \frac{(c0 + c1t + c2t^2)}{(1 + d1t + d2t^2 + d3t^3) + \varepsilon(p)} \\ &where, \\ &t = \sqrt{\ln\left(\frac{1}{(1 - P_d)^2}\right)} \end{aligned} \tag{7}$$

TABLE III Coefficients for the normal approximation

c0	2.515517
c1	0.802853
c2	0.010328
d1	1.432788
d2	0.189269
d3	0.001318

If Pd is 1.0 replace with 0.99999 and if Pd is zero replace with 0.00001.

3.2 MOTION EXPERIMENT PARTITION ANALYSIS

Looking at the data in Fig . 7 reveals that in each case the Pd increased with velocity. Increased detection probability with velocity follows intuition regarding the importance of motion as a visual cue. The following graphs are included to assist with the visualization of how the Pd values change with certain parameters but it must be kept in mind that the **Pd depends on all 4 factors**, not just a single factor or main effect.

Over all cases with targets present, the average Pd = 0.35. When we partition by background, we see that there was one background with high average Pd (#4, Pd = 0.54), one background with low average Pd (#12, Pd = 0.23), and the other three were close together (Pd close to 0.315), see Fig. 4 .

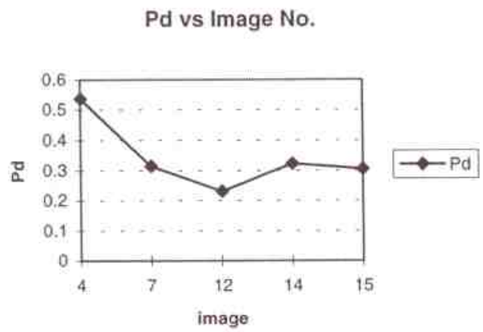

Fig. 4 Pd vs Background

When we partition by contrast level, we see that Pd is monotonically increasing with contrast from 0.30 to 0.40, see Fig. 5.

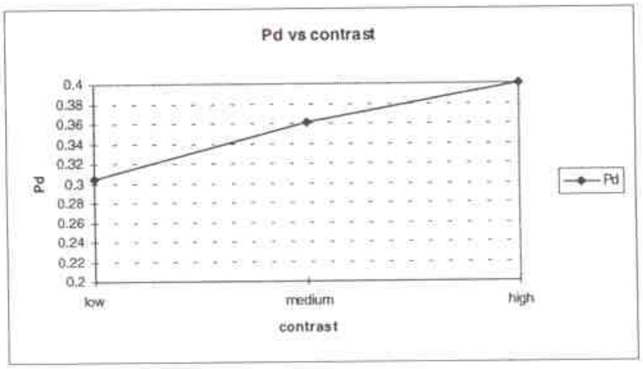

Fig. 5 Pd vs contrast

When we partition by range, we see that there was a consistent and large effect of increasing range, i.e., the effect of a 500 meter increment in range was strong at 1500 meters and was strong at 5500 meters. Pd at 1500 m was 0.65 and Pd at 6000m was 0.14, see Fig. 6.

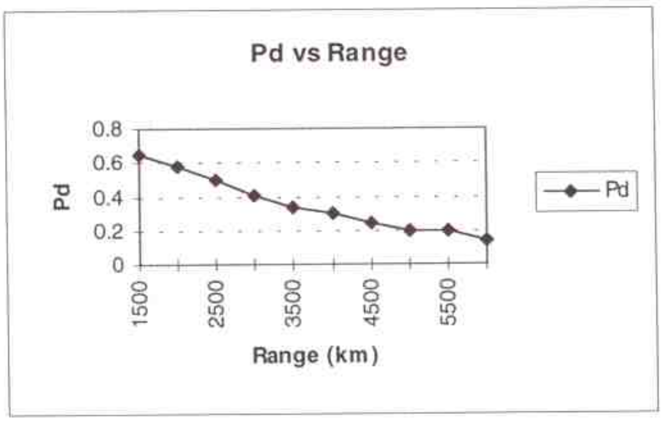

Fig. 6 Pd vs Range (km)

When we partition by ground velocity, we see a significant and monotonic increase in Pd with increasing velocity, from 0.24 for stationary targets to 0.46 for 20 kph targets, see Fig. 7.

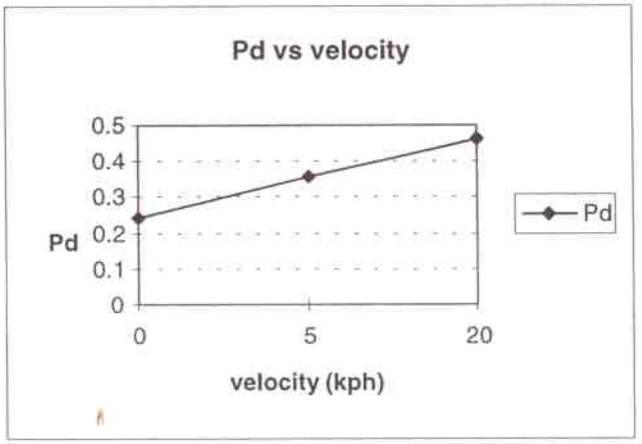

Fig. 7 Pd vs vehicle velocity (kph)

When we partition by velocity and contrast level, we see that Pd increases with increasing contrast at all speeds, and that Pd increases with increasing speed at all contrasts. Furthermore, the magnitude of the effect of speed is generally comparable at all contrasts, and the effect of contrast is generally comparable at all speeds, see Table IV.

Table IV Pd as a function of contrast and ground speed

Velocity (kph)	High Contrast	Medium Contrast	Low Contrast	Average Pd over contrast
0	0.279	0.235	0.215	0.243
5	0.403	0.372	0.295	0.357
20	0.512	0.477	0.402	0.463
Average Pd over velocity	0.400	0.361	0.304	0.354

When we partition by range and contrast level, we see that Pd increases with increasing contrast at all ranges, and that Pd decreases with increasing range at all contrasts. Furthermore, the magnitude of the effect of range is generally comparable at all contrasts, and the effect of contrast is generally comparable at all ranges as shown in Table V. As expected, the vehicle detection probability generally decreases with range as shown in Fig. 6, and the vehicle with the greatest speed, in this case 20 kph, always has a higher detection probability.

Table V: Pd as a function of contrast and range:

Range(km)	High	Med	Low	Avg
1500	0.700	0.637	0.615	0.650
2000	0.635	0.600	0.518	0.583
2500	0.588	0.469	0.441	0.500
3000	0.460	0.425	0.330	0.405
3500	0.390	0.348	0.257	0.331
4000	0.308	0.293	0.287	0.296
4500	0.263	0.268	0.186	0.239
5000	0.248	0.224	0.131	0.201
5500	0.231	0.200	0.160	0.196
6000	0.156	0.153	0.113	0.141
Avg	0.400	0.361	0.304	.354

Finally, Fig. 8 below shows how the Pd's for the vehicle varied as a function of velocity and range.

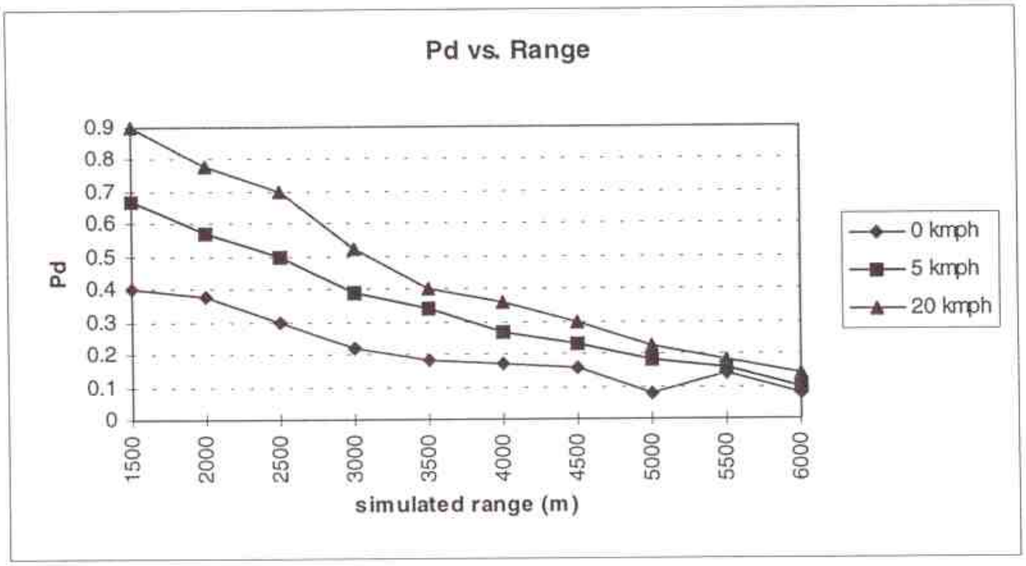

Fig. 8 Pd vs. range for three vehicle velocities

3.3 MOVING TARGET ALGORITHM

The 300 moving target trials were analyzed to determine an appropriate algorithm to represent the contribution of motion to the detection process. Three parameters of interest were taken into consideration: target angular extent, target to background contrast, and the target angular velocity. The following equation was used to predict the measured probabilities of detection:

$$\text{Probability of Detection} = \frac{(A/A_C)^{\varepsilon}}{1+(A/A_C)^{\epsilon}} \tag{8}$$

where A = target angular extent (mrad)

A_C = target angular extent necessary for 50% of the observers to detect the target

E = 2.7 + 0.7 (A/A_C).

A_C is a function of the target angular extent, the target to background contrast and the target angular velocity. The constants for A_C were determined by performing a linear regression on the moving target data from all 5 images (4, 7, 12, 14, and 15).

A comparison of the measured probabilities and predicted probabilities from the proposed algorithm was conducted. Figure 9 shows the measured data (x's) and the predicted probabilities (squares) as a function of the target angular extent. It is encouraging to see that the predicted data are well within the scatter of the measured data.

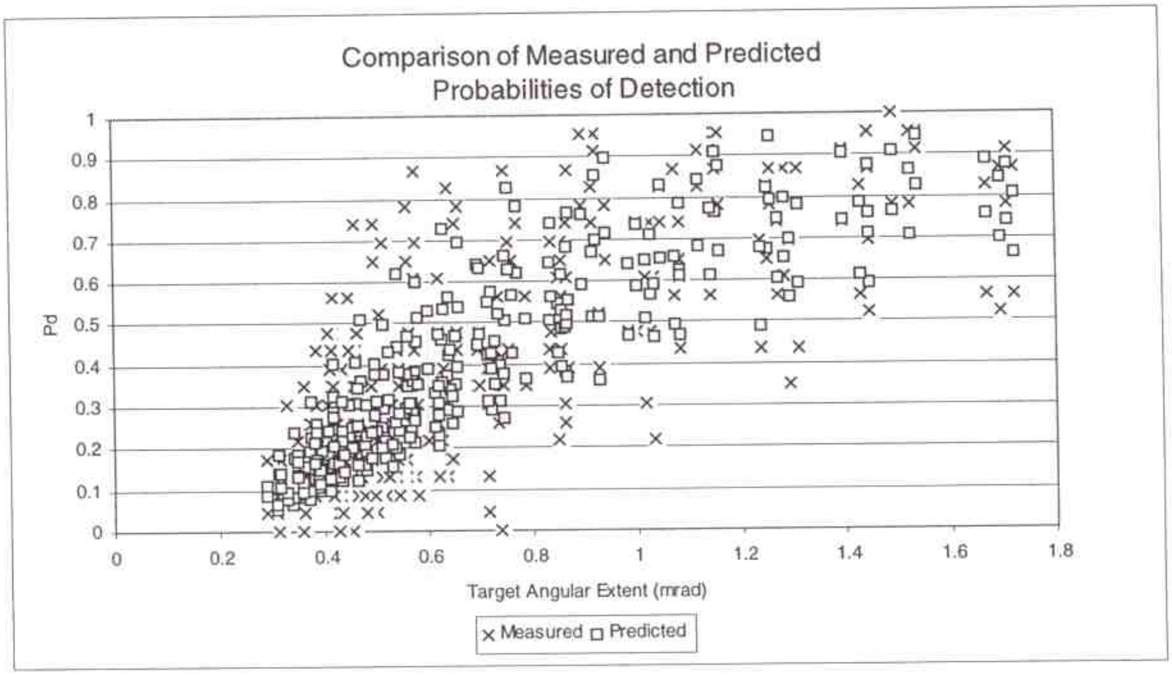

Fig. 9 Comparison of Measured and Predicted Probabilities of Detection for Moving Targets

Another way to visualize this comparison is shown in Figure 10. The predicted values are calculated from the new algorithm. The dashed lines represent the upper and lower 80 percent confidence bounds about the observer data.

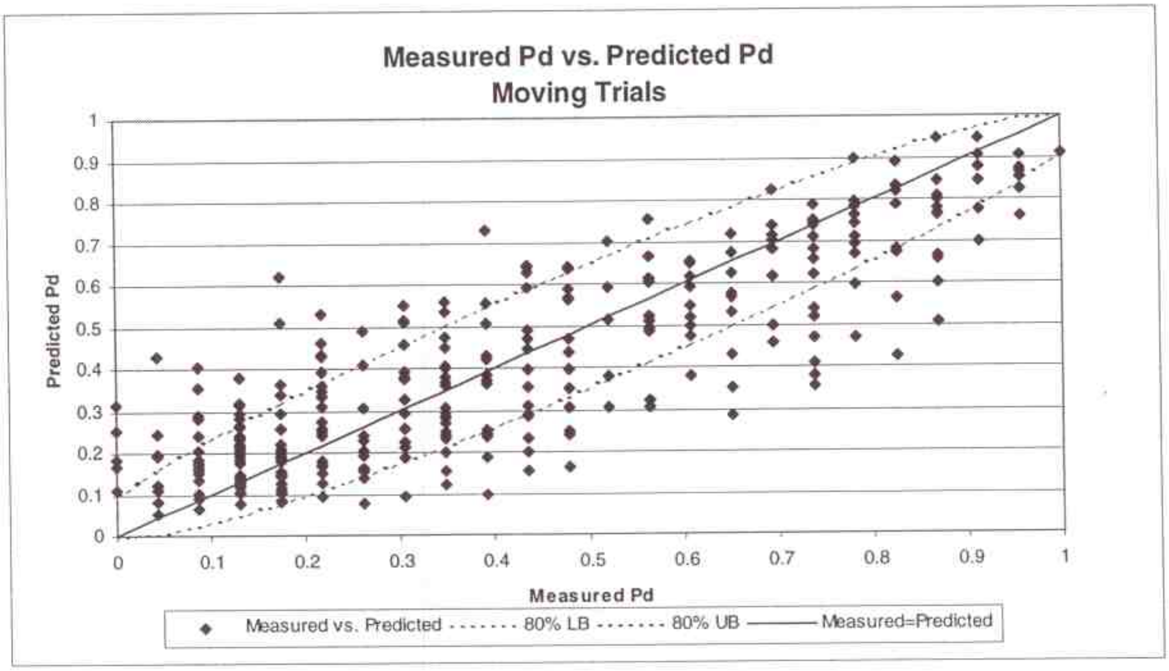

Fig. 10 Measured Pd. Vs. Predicted Pd for Targets with Motion

The proposed algorithm is shown to be a good predictor of the observer data. However, this should not be a surprise! It is now necessary to test the algorithm against other data sets to determine robustness.

4.0 FUZZY LOGIC ANALYSIS OF THE DATA

It has been three decades since Prof. L. A. Zadeh first proposed fuzzy set theory [8]. Following Mamdani and Assilian's pioneering work in applying the fuzzy logic approach to a steam engine in 1974 [9], fuzzy logic has been used in a growing number of applications. These applications include, transportation (subways, helicopters, automobiles (engines, brakes, transmission, and cruise control systems), washing machines, dryers, refrigerators, TVs, VCRs, and other industries including steel, chemical, power generation, aerospace, medical diagnosis systems, information technology, decision support and data analysis [10,11,12].

Our awareness of the visual world around us is a result of the perception, not only detection, of the spatio-temporal, spectra-photometric stimuli that is transmitted onto the photoreceptors on the retina [13]. The computational processes involved with perceptual vision can be considered as the process of linking generalized ideas or concepts to retinal, early vision data.

The theory behind the computation of target detection probabilities in the thermal and visible parts of the electromagnetic spectrum has been discussed in [14,15,16]. The theory of the fuzzy logic approach (FLA) and the application of the FLA to the problem of computing target acquisition probabilities to targets in both static infrared and visual scenes has been described in other papers [17,18,19]. The theory remains the same in this paper. The novel application of the FLA in this research was the inclusion of motion as one of the fuzzy logic parameters. A picture of the FIS used to analyze and model the data from this experiment is shown below in Fig. 11.

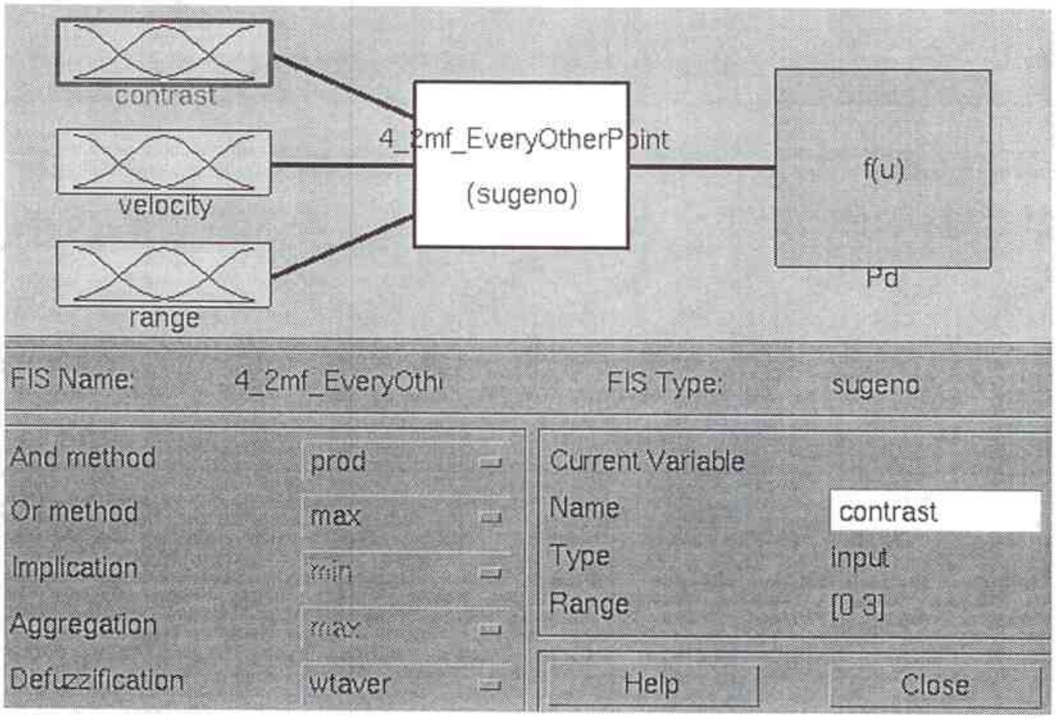

Fig. 11 Fuzzy Logic Inference System

On the left hand side of the system diagram in Fig. 11 are the three input variables, contrast, velocity and range. The center block of Fig. 11 shows the type of Fuzzy Logic Model used to represent the data. The far right hand side of Fig. 11 shows the output parameter which in this case was the probability of detection of the vehicles. In the training of this system, one half of the experimental perception data was used to build and train the FIS and the other half was used as checking data from which the correlation between model predicted Pd values and experimental Pd values was computed. The results show that the FLA and the Fuzzy Inference System (FIS) designed to include motion had 0.9 correlation to experimental data ***not used*** as training for the FIS. Training is an important term in this case, because the membership functions were not constructed manually, the membership functions were designed by using the Artificial Neural Network Fuzzy Inference System (ANFIS).[20] Fig. 12 is a representative plot of the experimental data modeled through the FIS and shows how velocity and distance from target to observer effected the Pd for one of the five kinds of backgrounds used.

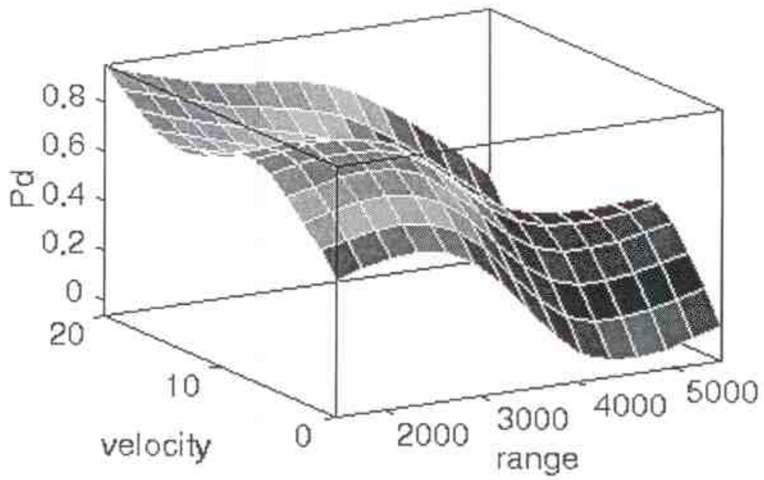

Fig. 12 Image 4 FIS surface showing relationship between range, Velocity and Pd.

4.2 CORRELATION OF FLA PREDICTED PD's TO EXPERIMENTAL PD'S OF MOVING TARGETS

The correlation values between the laboratory Pd values and the fuzzy logic model predicted values are shown below in Table VI and Fig. 13. The correlation of the FLA model to laboratory data ranged from 0.75 to 0.9, depending on the particular background, for data not used in the construction of the Fuzzy Inference System. In all there were 100 points per data set, 50 for training and 50 for checking the model and computing the correlation to experiment.

5.0. CONCLUSIONS

In conclusion, the FLA yields a correlation that approaches 0.9 between experimental values and model predictions and requires a fraction of the start-up effort that goes into traditional algorithm based techniques of modeling target acquisition probabilities. Furthermore, fuzzy-based solutions can be created in days or weeks in comparison to the years that may be needed to create a traditional solution. Since many groups have invested already quite heavily in the algorithm approach, we expect that the fuzzy modeling approach could be integrated into the statistical decision theory modules of existing target acquisition models.

The equation for the probability of detection was successfully modified to model the experimental visual perception data for moving targets. The modified equation includes the angular extent of the target.

The ANOVA has shown that **all the factors included in the experimental design are important at the 0.01 level of significance.** In other words, the target to background contrast, background type, velocity and range are all very significant and effect the Pd of moving targets to the same degree. **In addition, several second order interactions of these 4 factors are significant.** The second order interactions that are significant are; range and background, contrast and background, velocity and background, and velocity and range. Over the dynamic ranges in the experiment, range had the largest effect, followed by background, followed by speed, followed by contrast. However, if different levels of these factors were used in the experiment, the order-ranking may have been different.

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Euijung Sohn, studied at the University of Illinois and got her B.S. degree in Electrical Engineering. After her graduation, Mrs. Sohn was hired in Simulation department in U.S. Army Tank Automotive Command in 1991. She was involved in the various type of terrain simulation with the six degree of freedom moving simulator and analyzed the results from many test sensors. Mrs. Sohn has worked as a research engineer from 1992 to present 1995 in the Survivability Center. She has been involved in the validation, and verification of thermal and visual detection models and atmospheric propagation studies. Mrs. Sohn has co-authored several technical papers in the area of infrared and visual system simulations and target detection.