

Methodology for estimation of probable location of VRU before impact using data from post-crash analysis

Hariharan S Subramanian, Sudipto Mukherjee, Anoop Chawla, Dietmar Göhlich

Abstract The incidence pattern of vulnerable road user (VRU) injury is modified by the transport infrastructure on the ground. Recent improvements in modelling capability introduce the possibility of evaluating performance of safety measures by incorporating a distribution instead of a single standardized test. The question addressed in this work is to estimate the probability distribution of crash initiation modes based on post-crash observations.

A multi-body simulation based approach of using adaptive Markov Chain Monte Carlo (MCMC) sampling techniques implemented in statistical software “R” has been used. The two input variables under study were location of VRU along the lateral axis in front of vehicle and shape of vehicle front. The observed output was the locations of head hits on vehicle front profile.

Simulation studies on VRU head crash locations from the German In-depth Accident Study (GIDAS) with the severity of injury and the crash vehicle details have been used. These converge to a distribution with mean around the center plane of the vehicle with spread of around 30 cm in one standard deviation.

Keywords Monte Carlo, Pedestrian crash simulation, probability distribution

I. INTRODUCTION

In an engineering perspective, the safety of vulnerable road users (VRU)] remains an open challenge to be addressed owing to the difference in mass between vehicles and the VRU. The incidence pattern of VRU injury is modified by the transport infrastructure which includes factors like land use, traffic flow and vehicle design. The present work relates to the methodology to extract statistics of the configuration of initiation of crashes which contribute to injury to pedestrians.

Several crash databases around the world report the occurrences of severe to fatal vehicle-VRU crashes [1]. Pedestrians, being bereft of crash protective technology, constitute one of the more vulnerable categories of VRU along with cyclists and motorcyclists [2]. Pedestrian crashes with the front of a vehicle, in varied gait positions, have been reported as a frequent event [3].

Understanding of crash kinematics has led to improved predictions of crash behavior using computer simulations for VRU-to-vehicle crashes. Vehicle-front design for enhanced safety of pedestrians requires studies simulating the crashes. Multibody-based approaches using MADYMO have been used effectively for reconstructing pedestrian crashes to estimate the pre-crash conditions based on post-crash conditions of crashes recorded [4,5]. Studies using pedestrian models to predict kinematics of crashes when compared with Post Mortem Human Surrogate (PMHS) experiments indicate that computational models can replicate the kinematics of the PMHS experiment with significant accuracy [5,6]. Finite element models developed with muscle activations represent a way to replicate a more “human” like behavior compared to dummies and PMHS studies [7].

With FE pedestrian models, it is expected that replicating crashes will mimic real life cases better in the near term. Vehicle design engineers now have the opportunity to work with a range of crash scenarios and person-specific models in improving vehicle design. A pedestrian crash environment can be parameterized by the vehicle geometry and motion, relative position of pedestrian with respect to vehicle and pedestrian gait sequence prior to the crash event. Pedestrian location along the hood at the point of impact and the gait state influence the crash kinematics of the pedestrian. Significant variation in probability of injury, to the head and

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thorax in particular, is caused from a second impact with the vehicle. Therefore, a vehicle front design process needs an estimate of a representative distribution of the point of contact in typical pedestrian crashes.

It is emphasized that the distribution is sufficient, and the specific point of contacts in individual crash incidents obtained by detailed crash investigations, may not be of relevance. This is when the design is not based on limiting injuries for a small number of representative surrogates, or crash configuration, but across the entire crash statistics.

This work is an attempt to develop a methodology to estimate the position of a pedestrian in front of a vehicle for simulation studies with a prior knowledge of the outcome (head hit location) of a known number of crashes.

II. METHODS

A reverse Monte Carlo (MC) simulation is suggested since an output measure was available and one of the input quantities was to be estimated. An overview of the methodology adopted is shown in Fig 1. In the figure, the boxes with broken outline represent the unknowns. MADYMO multibody solver was used for predicting crash kinematics and consequently the head hit location for a specific contact location on the front of the car. The location of a specific head hit is influenced by the anthropometry of the pedestrian, relative angle of pedestrian to vehicle, gait position, relative velocity and relative location of the pedestrian along the lateral direction of vehicle.

For this study, relative velocity is assumed to be well approximated to vehicle velocity and it was assumed to be at 40kmph, which is a critical point in the fatality risk curve. It is also known that head hits can be quickly estimated by the wrap-around distance [WAD] with uncertainty driven by car shape and velocity amongst other factors. A band of 100-150 cm of WAD on a typical conventional internal combustion engine powered car in the GIDAS data suggests the usage of the 50th percentile male (50M) is representative of the population in GIDAS data, from the list of Madymo models available with us. The WAD is not used for any subsequent calculation.

The relative “angle of impact” defines the orientation of the pedestrian model with respect to the vehicle model. It is measured as the angle between projection on ground plane of the coronal plane of the pedestrian to longitudinal direction of the vehicle, referred to as θ_z in Fig 5 and Fig 6. A study by [8] provided incidences of crashes from the GIDAS database and data collected by the Traffic Administration, PR of China. The study also presents an estimate of variation in angle of VRU with respect to the vehicle from reconstructed VRU-vehicle crashes. The definition of “angle of impact” in the present study has been modified from the definition used by [8]. A simplification of the definition was made assuming the pedestrian was facing forward. It was also noted that [8] provides statistics on crash angles recorded and not detailed case studies. Reference [9] had also shown an application of the data collected in cases from [8] for studies on vehicle front design.

The state of a walking pedestrian is conventionally captured as a progression percentage through a cycle. The specific point along the gait cycle of the pedestrian at impact is known to influence the lateral shift in head hits across the vehicle. Studies by [10] have provided estimates of the influence for 50M multibody model from TNO[11] using MADYMO solver. In this study, the state of gait is assumed as an angle of 0.5 radian between the legs at the hip joint similar to the gait assumed for the 50th percentile male model in [12]. In the TNO pedestrian model, the angle of upper leg to body vertical plane can be specified using hip joint angle rotations and 0.25 radians were input to left and right leg.

MADYMO crash simulation results yield head hit locations which are measured similar to the technique used for plotting head hit locations in the GIDAS data. For this study, head hit location from MADYMO simulation was compared with GIDAS data to infer the contact location distribution. The quality of agreement of output from simulation to GIDAS data was measured by “Root mean square difference” (RMS) between generated MC values and GIDAS distribution. The overall process is outlined in Fig 1.

The input variable for the study, namely the pedestrian location, is assumed to follow a Gaussian (normal) distribution. The methodology does not change significantly if the distribution type has to be changed. Reverse Monte Carlo code aims to provide a better match indicated by a lower value of the RMS. Fig 1 shows the three input variables in the bottom row and processed output “RMS” on the top right.

For every pedestrian location, two simulations were performed, one each for left and right side hit with varied angles of inclination for both scenarios. Vehicle front model remains the same throughout one complete run of MC simulation and four different vehicle profiles were planned for this study.

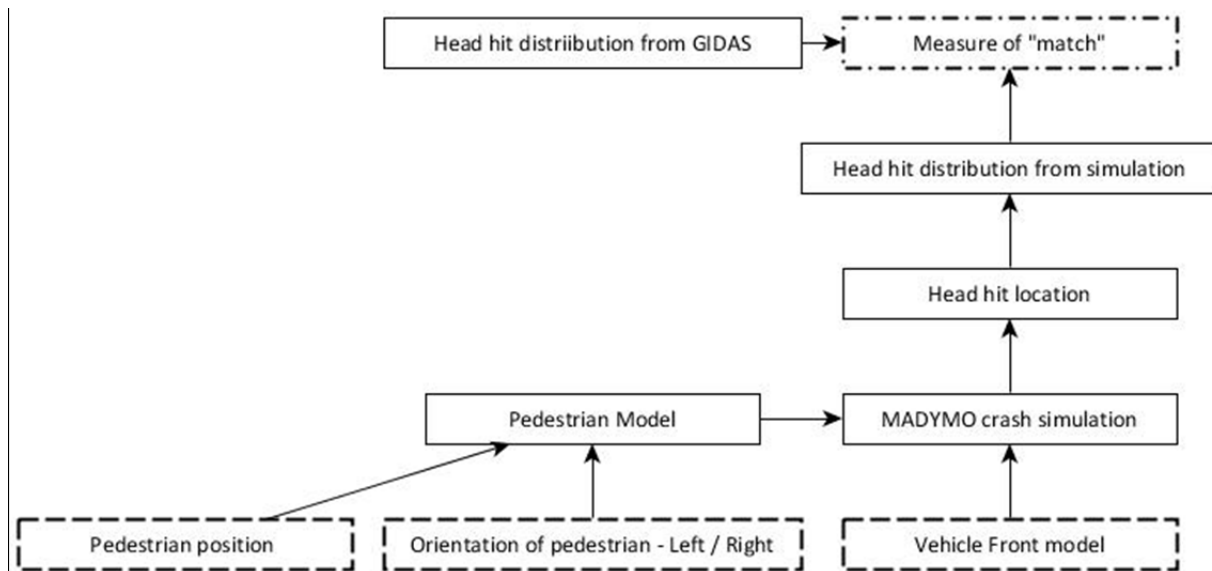


Fig 1 Methodology of vehicle-pedestrian crash simulation for Monte Carlo Simulation

Head hit data from GIDAS

Vehicle-pedestrian crashes recorded in GIDAS were obtained by reverse processing of images published in [2]. The number of head hit location points extracted (654) was less than the number of cases mentioned (759). This is a known limitation to the GIDAS dataset considered. This dataset contains a mixture of vehicles and mixture of VRU including pedestrians, motorcyclists and cyclists. Though an anomaly, it suffices for the limited objective of demonstrating the process of extracting useful data from an existing dataset to demonstrate the methodology.

GIDAS head hit data were processed by converting the scale used in [2] to have measurements as positive values along the lateral direction of vehicle instead of origin at central plane. The longitudinal axis of the vehicle was divided into bands of 50 cm each as in Fig 2. The band of 100 to 150 cm on the vehicle front profile was known from WAD-based studies to be the region with higher chances of head hits of 50M. The lateral dimension of the vehicle was also divided into bands of 10cm each. An assumption was that every vehicle would be placed with the central plane located at 100 cm on the scale.

Every head hit, indicated as dots on a representative vehicle profile in Fig 2, was recorded and grouped into segments of 10cm width each, resulting in a frequency distribution shown in Fig 3. The number of head hits extracted was normalized over the total number of head hits across the lateral direction leading to a density coefficient. These normalized density coefficients were considered the target for the reverse MC study planned.

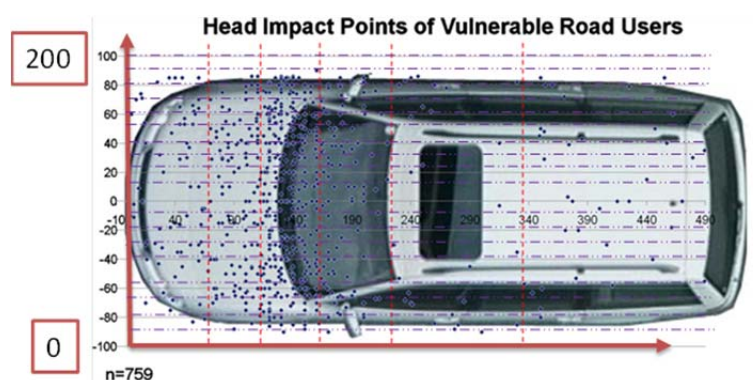


Fig 2 Vehicle figure from [2] edited for study

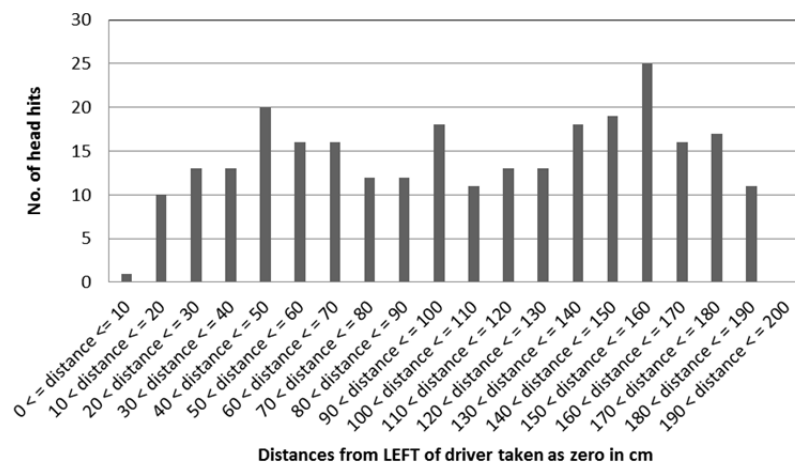


Fig 3 Head hit location frequency distribution along lateral direction of vehicle (0 to 200 cm) from GIDAS data in band located 100-150cm from front of vehicle

Vehicle –Pedestrian crash computational Model

Geometrically, the vehicle front profile was made to satisfy a representative vehicle profile. The only standard representative profile is specified in part 6 of ISO:13132 [13]. This was for simulation of a car-tomotorcycle crash. Apart from a “generic” car profile, 3 different vehicle front profiles, one each from European specification of segment A, B and D were modelled. Fig 4 shows 4 different vehicle profiles considered. Two compact segment cars and one sedan car front profile were considered along with a randomly generated “generic” profile. The variation was created so as to partially account for the lack of clarity on the output data.

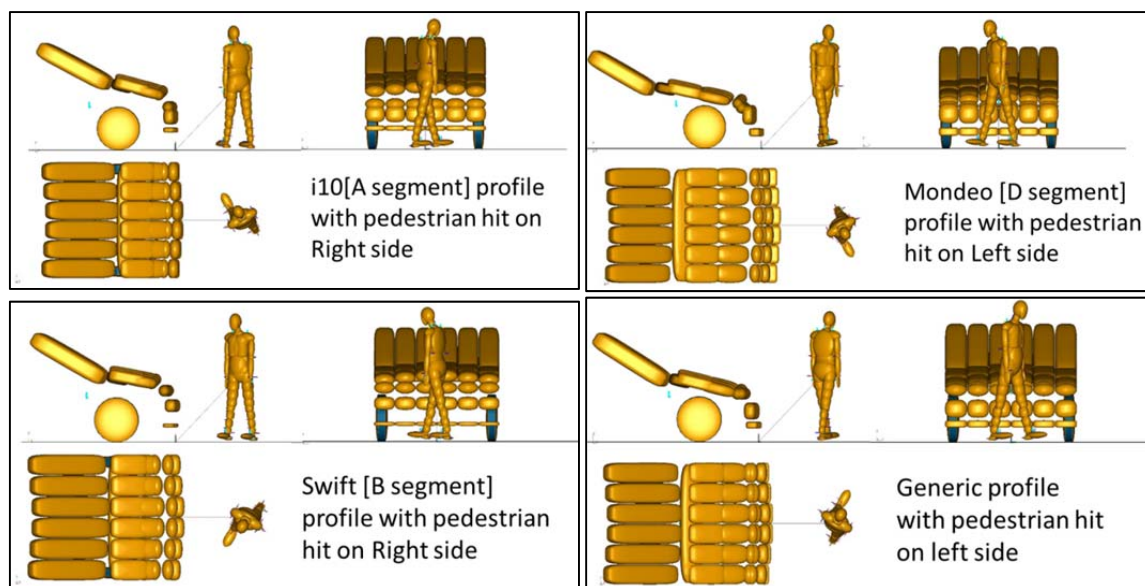


Fig 4 Four different vehicle profiles used in MC study with pedestrian orientation at left and right extreme positions

Vehicle-to-pedestrian crash scenario was computationally replicated using MADYMO. The vehicle was constructed with 6 segments along the lateral plane. Crash characteristics were modelled using the force-deflection curves for loading and unloading obtained by processing Euro-NCAP pedestrian test data over a 10-year period [14]. Bonnet, bonnet leading-edge and bumper shape along with windscreen were provided with green, red and yellow bands of force-deflection characteristics as estimated by [15]. The division of the vehicle laterally into 6 segments was based on the results formulated by [15].

Fig 5 and Fig 6 show the two basic simulation setups which were recreated for every initial position in the direction of X of the pedestrian model from TNO [11] represented as 50M. Two scenarios were needed to address non-symmetric distribution of crashes if required by the MC process. In both scenarios the struck leg was forward and gait was similar to the authors’ previous work [16].

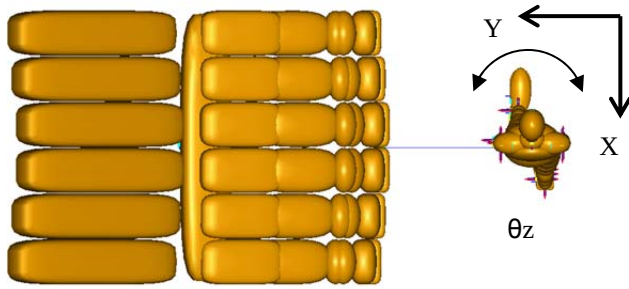


Fig 5 Vehicle pedestrian crash "Left" scenario

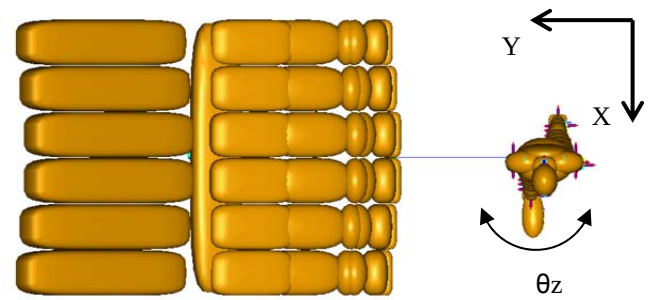


Fig 6 Vehicle pedestrian crash "Right" scenario

Monte Carlo Implementation

MC method implemented in R language using package FME by [17] was used in this work. The process of implementation has been outlined in Fig 8. The "R" code used for implementation has been provided in the Appendix.

Variation in left and right orientation of the pedestrian was end limited at $\pm 30^\circ$ and is centered at the nominal positions shown in Fig 5 and Fig 6. They have hence been treated as two separate inputs and two MADYMO "XML" input files, one each for "left" and "right" orientations of 50M, were generated. Range of " θ_z " values were 30° on right and left of pedestrian from the orientations indicated in Fig 7. The variation of the angles was assumed to be a normal distribution having a mean at indicated angles and a standard deviation of 15 degrees. This was an assumption derived from observed limits of angle of impact observed in [8], although the angle notations are different. The angle of the head has been extrapolated to be angle of pedestrians before crash so as to explore variation in pedestrian orientation. The second input variable was "pedestrian location" in "X" axis.

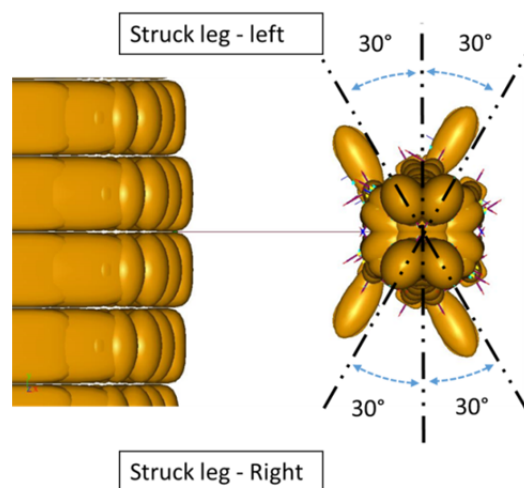


Fig 7 Angle limits of 50M used in MC study

These two inputs were incorporated into MADYMO XML input files to estimate head hit locations from MADYMO solver. Head hit location on the vehicle was computed by processing the "LPS" output files of MADYMO.

The head location in the "X" direction as indicated in Fig 5 and Fig 6 was written to an external file F1. F1 was initialized with inputs 0 to 200 in steps of 10 (0, 10, 20... 200) to act as an external storage or a global variable. The GIDAS frequency distribution processed in terms of density co-efficient was stored in file F2 to provide a reference for comparison. F1 was updated after every step. Values stored in file F1 were also processed for density co-efficient in same intervals as in F2 for every iteration, and the root mean square difference between the two was computed.

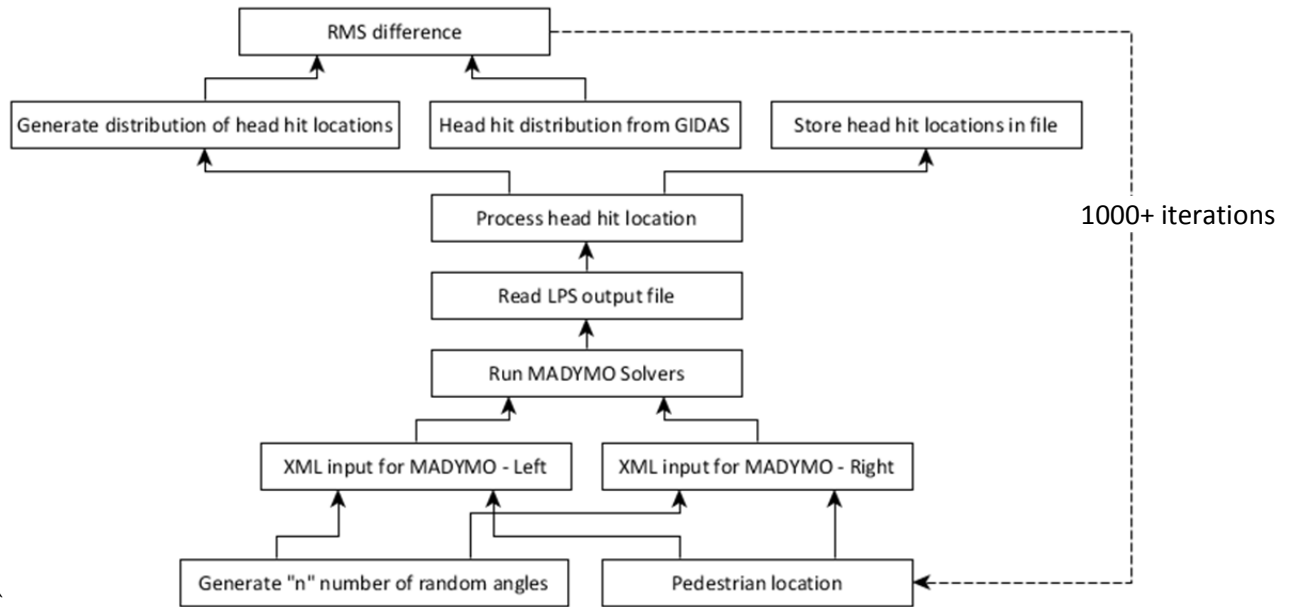


Fig 8 Overview of Monte Carlo process implemented in R

μ was defined output variable to be minimized using the MC study. It was computed as the expression in equation (1). A relaxation parameter (RP) equal to the probability of the outcome predicted by the distribution of the specific case being simulated in iterations was added. The details are in FME documentation [17]. In short, RP represents density of a normal function with logarithmic component added to increase the tail of the normal distribution. A detailed explanation of the computation of μ is provided in the Appendix along with Fig 12.

$$\mu = \text{RMS value} - \text{Relaxation Parameter} \quad (1)$$

FME package in “R” provides a module “modMCMC” with DRAM procedure. DRAM procedure allows for quicker and better convergence while using a Markov Chain MC (MCMC) simulation. The study was implemented using the DRAM procedure with MCMC simulations. Details of the core “R” code/parameters used are provided in the Appendix.

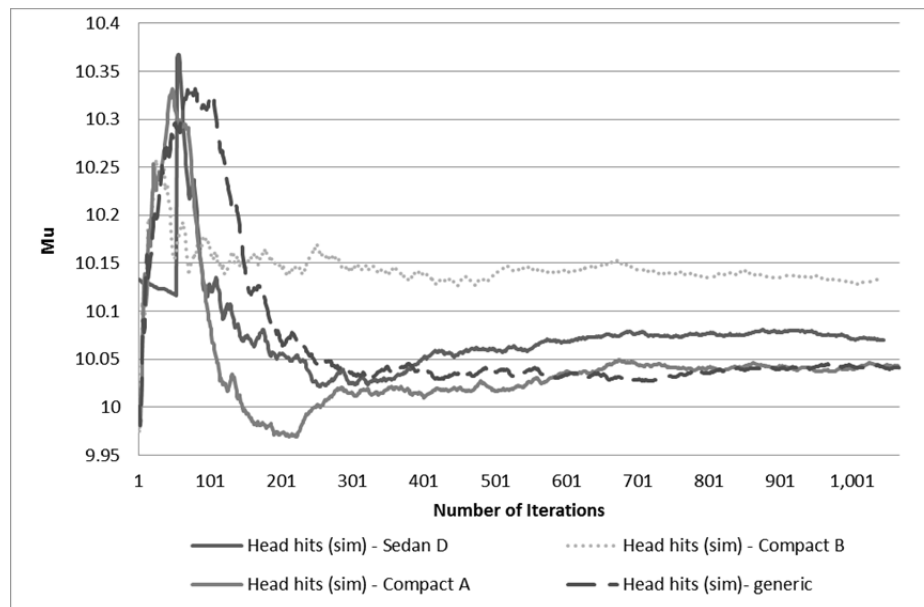
III. RESULTS

Variation of output variable μ

“ μ ” value was computed at the end of each step in the MC simulation and its progression was tracked through the entire iteration. Fig 9 shows a combined μ value variation for 4 different vehicle profiles under study. Abscissa denotes the number of iterations performed. All simulations were performed for planned 1000 iterations. DRAM procedure guides the actual number of iterations performed; hence, the number of simulations would vary around 1000 and not be exactly 1000.

All four MCMC simulations produced a variation of μ with plateau region post 300 iterations, where the iterations could have been stopped. An initial increase in μ was observed up to around 100 iterations followed by a decrease. “ μ ” value stabilized after 300 iterations and remained almost constant (less than 5% deviation) to 1000+ iterations.

The stabilization of μ value denotes a virtual “limit” to the process of matching of a generated MC head hit distribution with the given GIDAS distribution. The μ being centered on “10” is driven by the probability of the specific case used for this iteration. A lower value of RMS would mean a better match with the reference data distribution. μ has a RP factor to help in guiding towards lower RMS. The μ scale is to be viewed as a relative indicator and not an absolute scale.

Fig 9 Variation of μ over Monte Carlo process

Variation of Output – head hit location

The location of head impact on “X” direction of the pedestrian was converted to normalized distribution intervals of 10 cm, in the range of 0 to 200 cm. Fig 10 shows the distribution at the end of the last iteration of the MC study superposed on the GIDAS data. The grey shade denotes MC data and the dashed line indicates GIDAS data. Abscissa of the graph represents lateral distance from 0 to 200 cm [“0” located on driver’s left]. The 100 cm value in abscissa denotes the vehicle central plane.

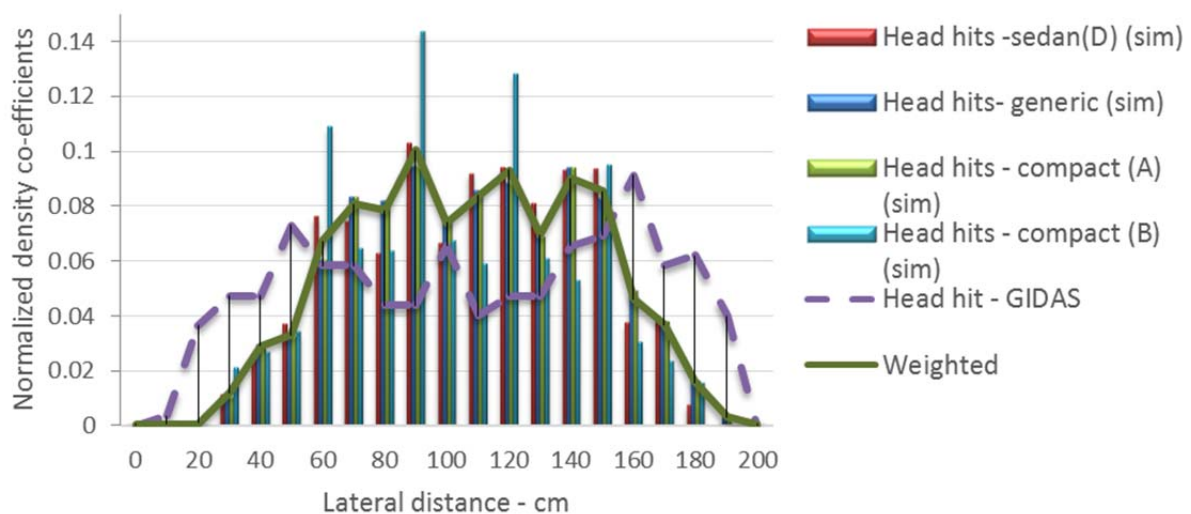


Fig 10 Variation of head hit distribution coefficients

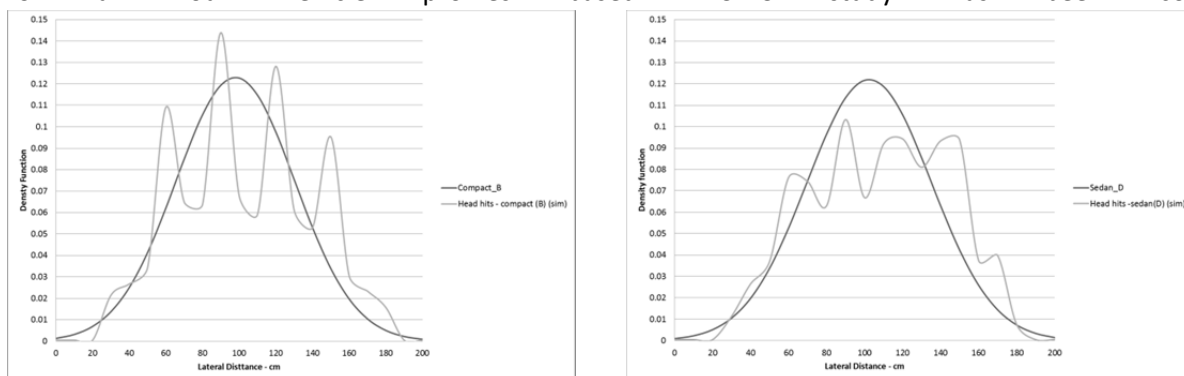
The previous figure is numerically captured in TABLE 1. The density coefficients sum up to 1 indicating that a normalized ratio was maintained. The Pearson coefficient was calculated with respect to the GIDAS data and it shows that vehicles with segment A and the generic profile have similar levels of “match” with GIDAS data.

TABLE 1
COMPARISON OF DENSITY COEFFICIENTS OBTAINED FOR VARIOUS VEHICLE PROFILES WITH GIDAS

Lateral distance(cm)	GIDAS reference	Segment A	Segment B	Segment D	Generic profile
0	0.001	0.000	0.000	0.000	0.000
10	0.003	0.000	0.000	0.000	0.000
20	0.006	0.001	0.000	0.000	0.001
30	0.011	0.011	0.021	0.011	0.011
40	0.021	0.030	0.027	0.027	0.030
50	0.034	0.032	0.034	0.037	0.032
60	0.052	0.061	0.109	0.076	0.061
70	0.073	0.083	0.065	0.074	0.083
80	0.094	0.082	0.064	0.063	0.082
90	0.110	0.095	0.144	0.103	0.095
100	0.118	0.076	0.068	0.067	0.076
110	0.116	0.086	0.059	0.092	0.086
120	0.104	0.089	0.128	0.094	0.089
130	0.086	0.069	0.061	0.081	0.069
140	0.065	0.094	0.053	0.093	0.094
150	0.045	0.083	0.095	0.094	0.083
160	0.028	0.049	0.030	0.037	0.049
170	0.016	0.038	0.023	0.040	0.038
180	0.009	0.017	0.016	0.008	0.017
190	0.004	0.004	0.000	0.000	0.004
200	0.002	0.000	0.000	0.000	0.000
TOTAL	0.998	1.000	1.000	1.000	1.000
PEARSON COEFFICIENT	1	0.505	0.367	0.457	0.505

Variation of Input Variable – Pedestrian Location

During every computation step of MCMC, a specific (distribution weighed random value) pedestrian location was generated by “modMCMC” module in R. This value was stored cumulatively to re-generate the distribution. The frequency distribution of initial pedestrian location along with corresponding Gaussian normal distribution for all four vehicle profiles based MCMC study has been compiled in



The distributions for Segment A and generic profile show a similarity in distributions whereas the other profiles show clear deviations. Segment B distribution has four peaks. Overall, there appears to be a consistent plateau region around the central plane and normal distribution approximation may not be the best starting model.

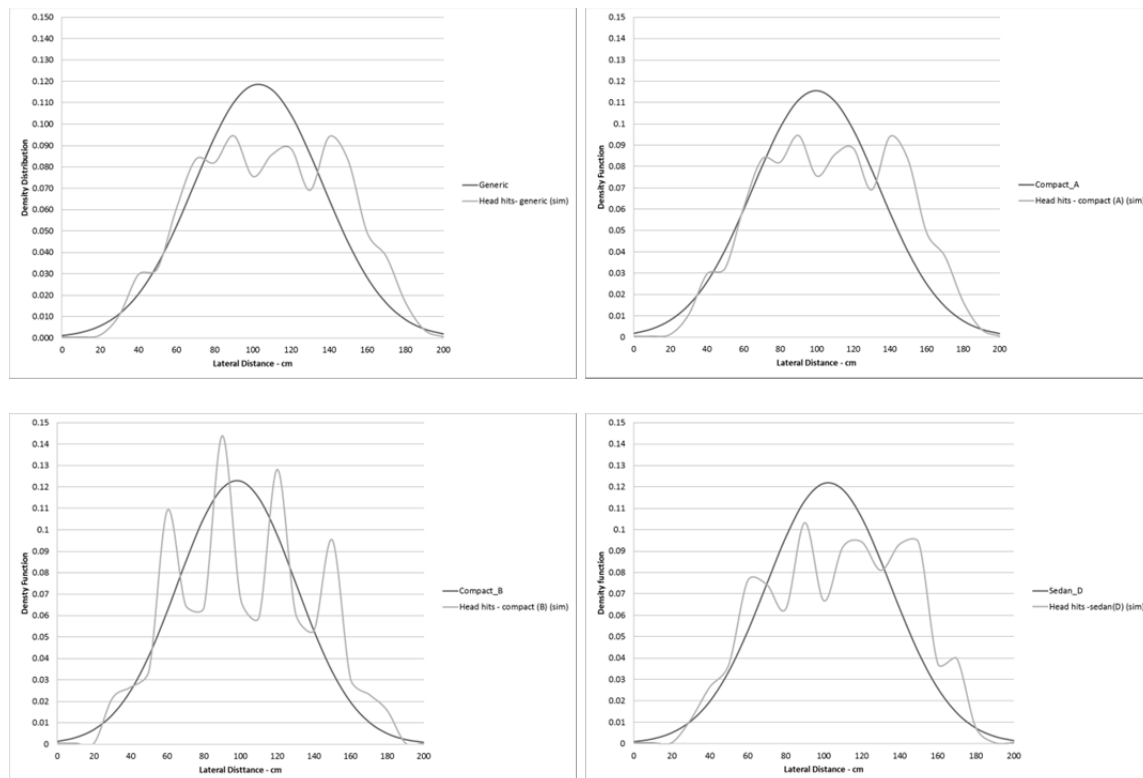


Fig 11 Variation of initial pedestrian positions with approximated normal distribution approximation

Fitting of data to a normal distribution was performed using “fitdistr” module in R. The module has closed form Maximum Likelihood Estimation with exact standard errors implemented for fitting to a normal distribution. Mean and standard deviation values for various vehicle profile-based MCMC simulation scenarios on pedestrian initial location are summarized in TABLE 2. The values indicate the mean around the central plane of the vehicle with roughly 30cm spread for one standard deviation.

TABLE 2
COMPARISON OF DENSITY COEFFICIENTS OBTAINED FOR VARIOUS VEHICLE PROFILES WITH GIDAS

	Mean (cm)	Standard Deviation (cm)
Generic	102.98	33.62
Segment A	99.64	34.51
Segment B	97.89	32.44
Segment D	102.40	32.71

IV. DISCUSSION

Head-hit data and simulation results comparison

The head-hit data from GIDAS compiled in Fig 10 appears to have higher density coefficients around 50cm and 160cm abscissae values, essentially a bi-modal distribution. We however estimate a plateau, or multiple peaks. Being shackled by lack of information of exact vehicle shape, impact speed amongst others, the estimates with a Pearson coefficient of 0.5 is in order, given that the variation is not linear.

We however have incorporated two groups, for pedestrian facing left or right of the car, with variation as shown in Fig 5 and Fig 6. The angle of the pedestrian was generated randomly from an assumed normal distribution of angles seeking a better “match” with GIDAS data. The effect of this model appears as the plateau variations in head-hit distance on both sides of a pedestrian location rather than a single side.

Implication of μ factor

“ μ ” value is also an indicator of fit of data to distribution. The role of the relaxation parameter was to condition the data with normal density factor along with RMS minimization. In a combined effect, the variation of μ factor was centered around a value of 10.

On comparing with a linear correlation coefficient such as the Pearson coefficient, it can be found that the distribution of head hits obtained by MCMC and the GIDAS reference do not exhibit a strong correlation. The same can be confirmed visually by observing plots of density coefficients. The existence of a weak correlation (≤ 0.8) suggests contribution of variables other than the ones considered in this study, such as variation in car shape. The maximum Pearson coefficient observed was 0.5 suggesting further work.

Population of car front profiles as a weighted sum

Further, the GIDAS database was known to have more factors contributing to it. Vehicle population to “match” data better with GIDAS was assumed as the weighted sum of four vehicle distributions already simulated in MCMC. An optimization problem was formulated as maximization of the Pearson coefficient and the best weighted sum has been shown in Fig 10. The Pearson coefficient did not improve significantly over the best vehicle profile response, indicating perhaps that further variables need to be examined.

Car front profiles and μ

The focus of this work was restricted to passenger car domain, thereby considering one vehicle profile each in A, B and D segments apart from a “generic” profile. With the four data sets, we were able to observe that the μ value in the plateau region of Segment B was highest among the four and the Pearson coefficient of Segment B density function with GIDAS data was the least at 0.367. For segment A and “generic” profiles, the plateau value of μ was least and they had the highest Pearson coefficient of 0.5. Segment D had an intermediate value in both.

Known Limitations

The role of pedestrian gait and relative velocity on the lateral spread of head hits across a vehicle has been previously established in studies such as [10]. This study did not consider the two variables. In principle, they represent a set of variables to be considered for this methodology. The focus was restricted to the role of vehicle design changes on the pedestrian head hit location as this methodology was driven by a larger research problem as part of a doctoral dissertation.

The GIDAS data chosen were from a set of vehicles having front profiles ranging from flat front to long bonnet. The speed at crash was not constant and the partner of crash with vehicles included all VRU. The limitations on the data processing and specificity were considered a positive note for the study since the methodology was intended to be used in scenarios where the estimation of input is not available due to lack of data.

Vehicle profiles have been modelled to replicate the significant points of interactions with pedestrians and do not represent any other features of vehicles.

The factors mentioned above limit this study to be a methodology demonstrator. Specific data on head hit location combined with vehicle front profile and pre-crash vehicle speed are being sought to validate the methodology.

V. CONCLUSIONS

The study demonstrates a method for estimation of distribution initial location of pedestrian based on a measure that quantifies the “match” to reference output data, in this case, the head hit location. Within the assumptions and limitations of the data set used in the study, a pedestrian located near the central plane of a vehicle laterally represents a higher probability and it reduces to a spread of 30cm on either side by a Gaussian distribution. The methodology introduces a tool to allow designers to deploy the flexibility of HBMs to design cars for the future without reducing the crash statistics to a small set of reference anthropometric models and scenarios.

VI. ACKNOWLEDGEMENT

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Appendix

Monte Carlo Study - computation of Mu

In this work, probability of occurrence of value from left extreme to μ computed at every step of MC under a normal probability curve constructed with known mean and standard deviation values. “dnorm” in R code represents the code to calculate normal density given by (2)

$$f(x) = 1/(\sqrt{2\pi}\sigma) e^{-(x-\mu)^2/(2\sigma^2)} \quad (2)$$

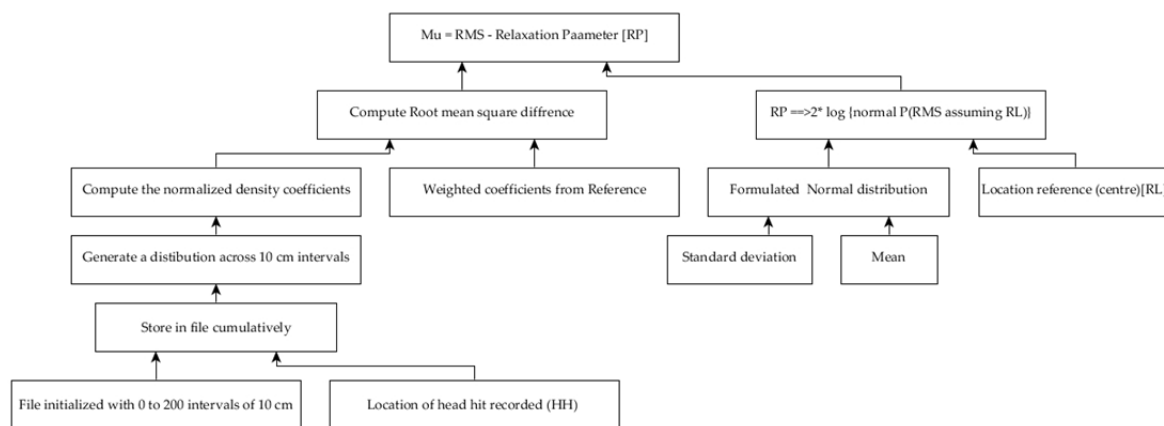


Fig 12 Method to compute μ

Mu variable was computed with the following expression in R for input to the module modMCMC.

```
mu <- rms*100 - 2*sum(log(dnorm(0, mean = mean_100_150, sd = sd_100_150))) #2*log(probability)
```

Where,

mu - parameter (output)
 rms - root mean square difference
 mean_100_150 - mean of normal fitted distribution (104.5)
 sd_100_150 - standard deviation (51.34)

Values for mean and standard deviation of the range 100 to 150 cm were computed from the values observed in GIDAS data.

Monte Carlo Study - “modMCMC” module in R

Monte Carlo methods implemented in FME package contains provision of Markov chain Monte Carlo [MCMC] with Delayed Rejection Adaptive MCMC capability. Following expression of code was used in R

```
MCMC <- modMCMC(f= Sim_SS, p = 0.45 , updatecov = 0.01*n, lower = -0.6, upper = 0.6, ntrydr = 3, niter = n, verbose = TRUE)
```

Where,

modMCMC - Calling function modMCMC function in FME package
 Sim_SS - Calling module for solver and computation of Mu
 updatecov - Number of iterations to update the covariance matrix [0.01*n]
 niter - Total number of iterations planned [n =1000]
 lower - Lower limit of the parameter [“-0.6” value implies 40 cm from vehicle center plane]

upper - Upper limit of the parameter [0.6 → 160 cm]
 verbose - verbose set to TRUE

Complete R code:

```
## no. of iterations
n <- 1000
## Generation of random variable values
ang_L<-rnorm(n,mean = 1.5708, sd = 0.2618)
ang_R<-rnorm(n,mean = 4.7124, sd = 0.2618)
Angle <- c(ang_L,ang_R)
cat("\n", file="Var_loop_1feb14.txt",append = TRUE )
cat(Angle, file="Var_loop_1feb14.txt",append = TRUE )
#Function for MC study
Sim_SS <- function(pos)
{
  c <- floor(runif(1, 1, n))
  #creating blank xml files
  file.create("car_ped_50_L.xml")
  file.create("car_ped_50_R.xml")
# reading files
  x1_50 <-readLines("xml_50.01", ok = TRUE, n = -1L)
  x2 <-readLines("xml.02", ok = TRUE, n = -1L)
  x3_50_L <-readLines("xml_50_L.03", ok = TRUE, warn = TRUE, n = -1L)
  x3_50_R <-readLines("xml_50_R.03", ok = TRUE, warn = TRUE, n = -1L)
  txt <- "\tVALUE =\n"
# creating xml file - 6c left
# creating xml file - 50 left
  write(x1_50[1:74], file= "car_ped_50_L.xml")
  cat(txt, file = "car_ped_50_L.xml", append = TRUE)
  cat(ang_L[c], file = "car_ped_50_L.xml", append = TRUE)
  write(x2[1:4], file = "car_ped_50_L.xml", append = TRUE)
  cat(txt, file = "car_ped_50_L.xml", append = TRUE)
  cat(pos, file = "car_ped_50_L.xml", append = TRUE)
  write(x3_50_L, file = "car_ped_50_L.xml", append = TRUE)
# creating xml file - 50 Right
  write(x1_50[1:74], file= "car_ped_50_R.xml")
  cat(txt, file = "car_ped_50_R.xml", append = TRUE)
  cat(ang_R[c], file = "car_ped_50_R.xml", append = TRUE)
  write(x2[1:4], file = "car_ped_50_R.xml", append = TRUE)
  cat(txt, file = "car_ped_50_R.xml", append = TRUE)
  cat(pos, file = "car_ped_50_R.xml", append = TRUE)
  write(x3_50_R, file = "car_ped_50_R.xml", append = TRUE)
#Process xml file in madymo and then in MATLAB for head distance
  shell("process_50.bat>log.txt")
# Process and create dis.txt
# % reading the output lps peak file
LPS_50_L <- scan(file ="car_ped_50_L.lps", what = "raw")
LPS_50_R <- scan(file ="car_ped_50_R.lps", what = "raw")
# Head distance calculation
# 50 M left and right
# initial
Head_X_50_L_i = as.numeric(LPS_50_L[75])
Head_X_50_R_i = as.numeric(LPS_50_R[75])
Head_Y_50_L_i = as.numeric(LPS_50_L[76])
Head_Y_50_R_i = as.numeric(LPS_50_R[76])
# final
Head_X_50_L_f = as.numeric(LPS_50_L[60975])
Head_X_50_R_f = as.numeric(LPS_50_R[60975])
Head_Y_50_L_f = as.numeric(LPS_50_L[60976])
Head_Y_50_R_f = as.numeric(LPS_50_R[60976])
Car_X_50_L_f = as.numeric(LPS_50_L[60979])
Car_X_50_R_f = as.numeric(LPS_50_R[60979])
Car_Y_50_L_f = as.numeric(LPS_50_L[60980])
Car_Y_50_R_f = as.numeric(LPS_50_R[60980])
```

```

# Distances
Dis_50_L_X = Head_X_50_L_f-Head_X_50_L_i;
Dis_50_R_X = Head_X_50_R_f-Head_X_50_R_i;
Dis_50_L_Y = Head_Y_50_L_f-Head_Y_50_L_i;
Dis_50_R_Y = Head_Y_50_R_f-Head_Y_50_R_i;
# X axis --> 0.04 is location of Bump lower , 0.08 semi axis
Dis_50_L_X = Car_X_50_L_f-Head_X_50_L_f-0.12;
Dis_50_R_X = Car_X_50_R_f-Head_X_50_R_f-0.12;
# Write an output file - dis.txt --> in cm
txt_L_50 <- c("50_L", " ", Dis_50_L_Y*100, Dis_50_L_X*100)
txt_R_50 <- c("50_R", " ", Dis_50_R_Y*100, Dis_50_R_X*100)
cat("\n", file="dis.txt", append = TRUE )
cat(txt_L_50, file="dis.txt", append = TRUE)
cat("\n", file="dis.txt", append = TRUE )
cat(txt_R_50, file="dis.txt", append = TRUE)
Dis <- data.frame(names = c("50_L", "50_R"),
values = c(Dis_50_L_Y*100, Dis_50_R_Y*100),
Xval = c(Dis_50_L_X*100, Dis_50_R_X*100))
# computing values
dis_ini_x_cm <- pos*100+100
dis_head_X_L_cm <- dis_ini_x_cm + Dis_50_L_Y*100 # Y in madymo is X in calc
dis_head_X_R_cm <- dis_ini_x_cm + Dis_50_R_Y*100 # Y in madymo is X in calc
# Comparing with approximate position of head hit from data
mean_100_150 <- 4.827
sd_100_150 <- 51.34
Data <- read.table("percent.txt", header=FALSE, col.names=c("val"))
hit <- read.table("start.txt", header=FALSE, col.names=c("val"))
breaks = seq(0, 200, by=10)
hits <- as.numeric(hit$val) # changing to number
a <- hist(hits, breaks, plot = FALSE)
Error = Data-a$density
Err <- as.numeric(Error$val)
rms <- sqrt(sum(Err^2)/length(Err)) # RMS value
mu <- rms*100 - 2*sum(log(dnorm(0, mean = mean_100_150, sd = sd_100_150))) # -2*log(probability)
# Adding new data to existing data and continuing process
cat("\n", file="start.txt", append = TRUE)
cat(dis_head_X_L_cm, file="start.txt", append = TRUE)
cat("\n", file="start.txt", append = TRUE)
cat(dis_head_X_R_cm, file="start.txt", append = TRUE)
# Writing values to files
Distance <- c(Dis$values, Dis$Xval)
# Distance_p <- c(mean_dis, sd_dis, mu, c, ang_L[c], ang_R[c], pos)
Distance_p <- c(mu, c, ang_L[c], ang_R[c], pos, a$density)
cat("\n", file="Var_dis_1feb14.txt", append = TRUE)
cat(Distance, file="Var_dis_1feb14.txt", append = TRUE)
cat("\n", file="Var_dis_processed_1feb14.txt", append = TRUE)
cat(Distance_p, file="Var_dis_processed_1feb14.txt", append = TRUE)
# removing "dis.txt"
# file.remove("dis.txt")
return(mu)
}
# set work directory back to "pedestrian location"
setwd("path/work_dir")
getwd()
## The adaptive Metropolis with delayed rejection
MCMC <- modMCMC(f= Sim_SS, p = 0.45 , updatecov = 0.01*n,
lower = -0.6, upper = 0.6,
ntrydr = 3, niter = n, verbose = TRUE)
plot(MCMC, mfrow=NULL, main="DRAM")
hist(MCMC, Full = FALSE, which = 1:ncol(MCMC$pars))
#par(mfrow=c(2,2))
plot(MCMC$pars, main="DRAM")

```