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INTRODUCING AGE-BASED PARAMETERS INTO SIMULATIONS OF CROWD DYMANICS

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ABSTRACT

Very few crowds consist of individuals who are exactly the same. Defining variables, such as age, and how they affect an individual's movement, could increase realism in simulations of crowd movement. In this paper, we present and discuss how age variations of individuals can be included in crowd simulations. Starting with the Helbing, Molnar, Farkas, and Vicsek model (HMFV), we modeled age differences by modifying the strength of the existing social forces. We created simulation scenarios with the varied strengths and used multiple approaches for validation, including experts' subjective validation and experimental validation via comparison of model predictions with observed crowd movements. The results indicated that individual characteristics such as age can be modeled by social forces Future extensions of our work would be to include individuals, small subgroups, and/or large groups of people to model multicultural crowd behavior.

1 BACKGROUND

There have been a number of previous attempts to model the behavior of large groups of people. Previous work in the modeling of virtual crowds has used one of two approaches. The first of these has been an attempt to model the behavior of the crowd at the group level, that is as a whole (i.e., as one collective) or as an assembly of a few, large subgroups (i.e., groups in the order of 100+ individuals). This has been the approach used for the SULNT software tool (Varner et al. 1998) in which behavior is not defined at the individual person level, but at the crowd/large group level.

The second approach to modeling crowd behaviors has centered on attempts to generate "emergent" crowd behaviors by using simple rule sets that describe the behaviors of individual, but interacting agents. In this approach, which, for example, has been used in the European "CROSSES" (Crowd Simulation System for Emergency Situations) project (see Ulicny and Thalmann 2001), every individual member of a crowd follows a small set of behavioral rules, and crowd behavior emerges as the result of the simultaneous actions of many individuals.

Both approaches to modeling virtual crowds have restrictions with respect to computational cost. Modeling a crowd "as a whole" allows a more complex set of behavioral rules to be specified at reasonable computational cost (e.g., "flocking"). However, this approach does not produce good results, except in relatively uninteresting situations such as textbook troop movements, herds, flocks and schools of animals, un-congested highway traffic flow, and other "normal" situations.

Modeling individuals, on the other hand, appears to be more face valid than a model of one homogeneous collective. A recent and highly successful example of this was in the massive battle scenes in the "Lord of the Rings" movie series, where individual warriors were controlled by production rule-based agents that responded to their local emerging situation to produce realistic ebb and flow of action in both the foreground and background for a massive number of players. There have been a number of advances in technology for building computer-generated forces

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(CGFs) for the military, and the movie industry has discovered that it can replace large groups of paid extras in crowd scenes by using sophisticated agent-controlled characters. Current military CGFs are satisfactory for many applications and getting better, but further advances would benefit greatly from more complex individual models and more realistic interaction models.

In contrast, the approach of modeling rule sets for individuals allows only relatively simple rule sets to be modeled in each individual agent before the computational costs become too large. While the entertainment industry and a number of CGF applications have shown good results using simple rule sets and dynamic interaction to produce complex crowd behavior (McKenzie et al. 2007), the lack of complex human response models has been a limitation. For example, since the large groups of movie warriors in the "Lord of the Rings" movies may all have the same objectives and responses, this approach of modeling individuals could lead to satisfactory results in this instance.

At the same time, homogeneity of goals and responses is not found in most human assemblages. Instead, "interesting crowd behaviors" will likely require the incorporation of more complex models that incorporate rich and realistic cues, such as gender, cultural norms and expectations, and social responses. Additionally, the heterogeneity of most crowds requires multiple state models for individuals to create truly useful predictions. Obviously, the computational costs to produce emergent group behavior can be very high, but this is probably the only effective way to produce really useful results in interesting applications beyond simple flock, herd and school approaches.

2 MODELING CROWD MOVEMENT

One particular aspect of crowd modeling is the description and prediction of crowd movement. These simulations represent complex interactions between individuals and their physical environments. They attempt to predict pedestrian movement in both normal and panic situations. Techniques like this can be used for planning of building construction and landscaping along with training for crowd control. When properly executed, simulations and models of crowd movement result in collective pedestrian behaviors that emerge due to complex interactions between individuals.

A primary method of modeling crowd movement is the Social Force Model (Helbing, Molnar and Schweitzer 1998). Social Force Models are rooted in the 'generalized behavior concept;' that is, for a model of crowd movement to be reliable, it does not need to model any certain individual correctly – just the average behavior of a group of individuals responding to certain forces. Social Forces Models assume that since pedestrians face similar movement and route choice decisions everyday, their reactions to certain stimuli are essentially automatic and can therefore be predictable. In order to mathematically model pedestrian movement, the assumption that a person's behavior will exhibit certain regularities must be made. This supposition is based on the assumption that an individual will make the optimum decision when making movement choices. With the acceptance of these two premises (i.e., that pedestrians' exhibit regular behaviors and individuals will make the optimum decision), a general mathematical model of human behavior can be formed.

Helbing et al. (2002) proposed the HMFV model, a social forces model, which is a self-driven, many-particles model using push-pull effects to describe pedestrian behavior in crowds. Each individual's behavior is influenced by a driving force, social interaction forces, and physical contact forces. The HMFV model for pedestrian motion uses parameters for social and physical forces acting on an individual to create a mathematical equation of motion, similar to Newtonian mechanics (Bierlaire 2003).

The HMFV model is one of the most popular social force models used for pedestrian movement. In this model, individuals start with a preferred speed and direction that is adjusted by interactions with the surrounding environment as the simulation runs. Driving forces cause the individual to move towards given attraction points, such as an exit of a room, or toward some goal. Social forces are attractive and repulsive forces calculated between an individual and any nearby individuals and obstacles. Note that driving forces and social forces seem to be "action-at-a-distance" forces. However, the cycle of action as viewed from the point of view of the individual is: observation, decision or reaction, and then action. Thus, it is more correct to view these forces as forces which the individual places on his body, in order to force his body to move as in an automatic reaction to a stimulus or in the manner he has decided upon, based on the observed circumstances at hand. There are also physical forces, which come into play when an individual comes into physical contact with another individual/obstacle. (These forces are real physical forces, in contrast to the driving and social forces, which arise from considerations of the individual due to his reactions and/or decisions.)

There are several important differences between the equations of motion used in the HMFV model and the mechanical equations of motion from physics. First, as mentioned above, social forces do not obey the usual Newtonian law of action-reaction. This is obvious when one considers an individual walking around an obstacle. Of course, there will be action-reaction between his feet and the floor, and action-reaction between his muscles and bones. However, there will be no measurable reaction force on the obstacle. Second, energy and momentum will similarly not be conserved. Third, particles (e.g. individuals) will internally produce social forces on themselves according to what they observe in the environment, with these forces causing changes in the individual's motion.

Fourth, there is no momentum transfer between the particles or between a particle and an obstacle, although momentum changes do occur. Rather, one observes that the social forces arise out of an information exchange between the particle and the environment (e.g. individuals aware of other individuals or obstacles).

The HMFV model describes pedestrian behavior mathematically by letting objects (pedestrians) be subjected to an acceleration term (driving force) and repulsive or attractive forces being generated by other individuals and physical boundaries. The driving and repulsive forces that compose the social forces acting on an agent are designed to follow the rules that (a) the individual wants to walk in a desired direction at a desired speed, (b) individuals attempt to maintain a preferred distance from borders or obstacles, and (c) the actions of other pedestrians will influence the actions of the individual by causing individuals to undertake avoidance maneuvers and adjusting their desired direction and speed to maintain a certain distance (based on situation) from other individuals. If crowd density increases to such an extent that physical contact cannot be avoided, then physical contact forces such as push and friction come into play and contribute to the equations of motion governing pedestrian movement. Interactions with obstacles and other individuals are characterized by avoidance maneuvers wherein the actual speed and direction of the individual differs from their desired speed and direction. During the time periods when an individual is not engaged in some type of avoidance maneuver, it is assumed that they will then seek to re-attain their desired speed and direction.

The objective of our effort is to produce more sophisticated models and computer representations of individual movement patterns and group interaction patterns. As discussed in the next section, our approach involves a variety of individuals and small groups of people with varying gender, cultural, and social backgrounds that encounter crowd situations differing in fidelity and a number of other determinants, such as setting, location, purpose, etc.

3 PROCEDURE

Instead of having a single homogenous crowd of individuals, a heterogeneous mix of individuals should be used to model a more realistic crowd. As a first approach, let us only consider introducing age based characteristics, and then consider how age would modify the current forces acting on an individual.

Starting with the Helbing, Molnar, Farkas, and Vicsek model (HMFV Model), the forces acting on an individual are:

1. Physical repulsive contact force of wall on individual,
2. Physical frictional contact force of wall on individual,
3. Social force of wall on individual,
4. Physical repulsive contact force of individual on individual,
5. Physical frictional contact force of individual on individual,
6. Social force of individual on individual,
7. Self propelling social force arising from any attraction point,
8. Small random forces included for variations.

(In items 1 and 2 above, the "physical repulsive contact force" is known in mechanics as the "normal contact force" while the "physical frictional contact force" is known as the "tangential (frictional) force". In item 7 above, an "attraction point" is some point that the individual is seeking to move to.)

Our approach is to model age differences by modifying the strengths of the existing social forces. Let us take as age groups; young children (ages 3 to 8), middle aged individuals (ages 18-40), and older individuals (ages over 70). Let us consider the following characteristics and how they might vary between each age group:

1. Personal Space (How close is an individual willing to be in relation to obstacles or other individuals),
2. Speed (How fast does an individual prefer to move),
3. Randomness (How random is an individual's motion).

As one will note, the characteristics of the above three different age groups are generally known to be sufficiently distinct as to present noticeable differences in their respective movements.

Let us take the middle aged group to be the mainline for which the original simulation parameters were constructed. For children, we would expect to see them making more erratic movements, and tending to move faster than the other groups. In addition, children would generally be willing to get much closer to both obstacles and other individuals. The older individuals would tend to move more slowly and be much more conscious of the spacing between themselves and others. These considerations give one a starting point for the construction of parameter sets for the three different age groups.

4 IMPLEMENTATION

The implementation of the above can be done by appropriately modifying the strength of each social force according to the age of the individual. Each of the three above characteristics can be associated with one or more components of the social forces acting on an individual. The simplest modification would be to just multiply the appropriate strengths by appropriate numerical factors. The problem then becomes how to determine these numerical factors. Source code for running the simulation in the Mason java-based framework can be found at Oleson and Kaup (2008).

To determine these numerical factors, we set up a standard simulation, and varied the multiplicative factors until the simulated behavior was as one expected and as observed among individuals of that group. For example, consider first the personal space of an individual. The forces which are affected by this characteristic are the social forces of wall to individual and individual to individual. This force is a repulsive force; so we increased it if the personal space should be greater and decreased it if the personal space should be smaller. For children, we took the personal space to be a fractional component starting at unity and reduced it until the simulation visually matched what we would expect to see for children running around in a room. Then the same technique was repeated for the older age groups, again starting at unity and increasing the parameter value until the simulation matched expectations. Next, we considered the speed at which individuals tend to move. Following the same procedure as used with the above personal space modifications, we used as the baseline the speed for the middle-aged group. A single frame from the baseline simulation is shown in Figure 1 to give an idea of the nature of the results. The speed for the younger age group was increased to around twice that of the baseline. The results for this younger group are represented by a frame from the simulation shown in Figure 2. Because of the greater speed of the younger individuals the crowd is less dense than the baseline crowd.

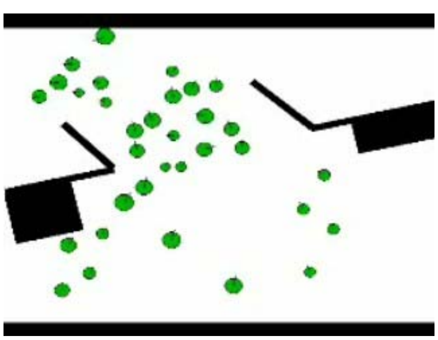

Figure 1: Single frame from a simulation of baseline group crowd.

The adjustment of the speed for the oldest group was found to be best at around half the speed of the baseline group. Just as the younger group is less dense, the slower speed of the older crowd leads to a denser crowd.

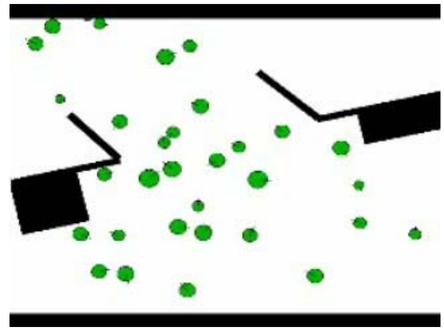

Figure 2: Frame from a simulation of crowd containing young individuals only.

Finally, we set the randomness factor for the two new age groups. The randomness for the younger group was found to be most realistic at around six times that of the baseline group. For the older group, it was found to be best at around half the randomness of the baseline group. Figure 3 shows a frame from a simulation of a crowd of older individuals.

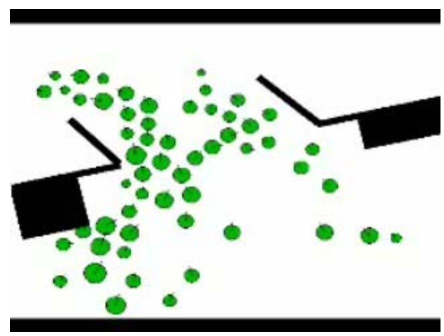

Figure 3: Frame from a simulation of crowd containing older individuals only.

Once "reasonable" values were established for the parameters, we then create several simulation scenarios depicting each of the three groups considered. The viewing of these simulations verified that we had generally captured what seemed to be characteristic age behaviors.

5 EXPERIMENTATION

In order to establish some validity of the simulations based on the HMFV model and our extensions to it, videos of movement within real crowds was obtained. It should be noted that although one would naturally expect that with the hours of TV and newsreel videos of events involving crowds which have been made, there might be at least a few of them that would provide a source of data to assist in determining parameters for various groupings. However what happens is that cinematic and editorial considerations dictate differently. In order to have video data for determining crowd parameters, what is needed is a fixed camera observing crowd behavior for an extended period of time. On the other hand, the TV and newsreel camera operators must zoom and pan through the crowd to focus on events of interest. As a result, such videos of crowd behavior as a whole are observable for at most a few seconds in most news videos and thus are essentially useless for model verification purposes.

Instead, we have generated our own videos by videoing events accessible for videotaping within institutional review board (IRB) guidelines. We have been able to attend such events and tape them from a fixed location and viewpoint so that long-term comparisons of actual crowd motion with simulations could be possible. Figure 4 shows a frame of video taken of the crowd exiting the Orlando Citrus Bowl stadium after a UCF-Tulane (American) football game. This frame was taken at the end of the game and thus is likely a mix of older and younger people. In contrast the frame in Figure 5 was captured 5 minutes before the end of the game and likely contains younger individuals. In a similar way the frame in Figure 6 was taken five minutes after the game and arguably contained older, slower individuals.

Figure 4: Frame captured from video of crowd leaving a UCF-Tulane football game at precisely the end of the game.

Figure 5: Frame captured from video of crowd leaving a UCF-Tulane football game 5 minutes before the end of the game.

Figure 6: Frame captured from video of crowd leaving a UCF-Tulane football game 5 minutes after the end of the game.

The above comments suggest comparisons between the baseline simulation shown in Figure 1 with the video frame in Figure 4, the young-individual simulation in Figure 2 with the video frame in Figure 5 and the older-individual simulation in Figure 3 with the video frame in Figure 6. Lacking further precise demographic data of the attendance at the game, these comparisons are necessarily only approximate. However the comparisons are favorable, supporting the hypothesis that our modeling technique does generate simulations which do appear to model age effects in crowds.

In order to make more quantitative comparisons between this video and the model predictions possible, the video tape has been processed so as to extract optical flow data using the Lucas-Kanade algorithm (Lucas and Kanade 1981) with the Open-CV (Intel 2001) image processing environment. The results of processing the video stream for a time interval centered on the frame shown in Figure 4 are shown in Figure 7.

Comparing Figure 4 and Figure 7, it is evident that the Lucas-Kanade optical flow captures the motion of the crowd upward and to left through the exist gate. Interesting subflows and "eddies" are also evident in Figure 7. The optical flow obtained from the video has not yet been precisely calibrated. Work is ongoing to calibrate the optical flow by comparing it with the results of a manual hand-counting analysis of the motion of individuals within the video.

Once the optical flow would be calibrated and corrections made for camera perspective, the observed data will be compared against simulations of the HMFV and other models. The model parameters that would best match the observed crowd behavior statistically could then be determined.

In addition to a number of football-game crowds, videos have also been taken at Universal Studios (an Orlando area tourist attraction) and at a local church which carries separate services for Hispanic and Non-Hispanic attendees. The variety of venues that we have found and the different types of people in these crowds should provide significant variation for realistic standardization of the values of model parameters as functions of age, gender, and culture. Of these varieties, we note that the football-game data are fairly age homogenous, being comprised mostly of a college-age population and middle-aged and older football fans. Conversely, Universal Studio's data are more a mixed age population, including children who would be with parents and grandparents, etc. Comparing how the age model performs for these two cases will obviously be useful.

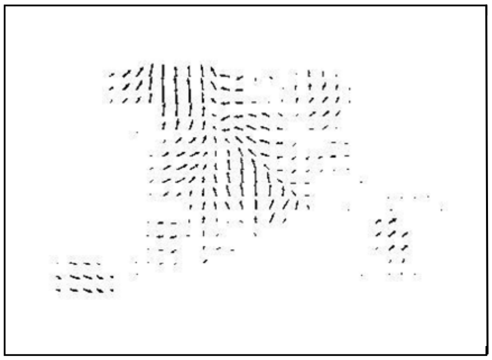

Figure 7: Optical flow vector field calculated from video illustrated in Figure 4. The vector scale is arbitrary.

A particularly interesting data set was obtained at the above-mentioned local church. Videos have been taken of the congregations exiting two different services: an early morning English language service and a later morning Spanish language service. The ethnicity of these two crowds is significantly different but also known. Comparisons among these videos are naturally expected to provide us with information on how we can include ethnicity factors into the various model parameters.

6 RESULTS

Characteristics of individuals, such as age, can be incorporated by modifying the strengths of the attractive and repulsive driving and social forces already existing in the model. These modifications have been done on a group level, in that all individuals of a group are given the same parameter values, which define how the individuals in that group tend to react to environmental factors.

7 FUTURE EXTENSIONS

Further work is to be done to gain more detail in how these characteristic groupings can be used and how different groupings might interact with each other. Using this technique, we can extend it to model individuals belonging to different characteristic groups (such as age and sex or ethnicity). Obvious questions that will need to be addressed are how to handle multiple modifications on the various forces. Further extensions would include allowing these modifications to be further modified by other events occurring in the environment.

A key issue for all approaches to crowd modeling is validity. Recent social science research has questioned both the "one collective" and the "interacting individuals" views of behavior in crowds (Kendig 2001) and points to a potential mitigating approach to modeling crowds using individual behaviors. It is thought that crowds consist of small "companion clusters" (3-10 individuals) that join and leave crowds together and may act locally in a more coherent way than completely independent individuals. Indeed, as Loscos, Marchal, and Meyer (2003) have pointed out, less than half of the pedestrians in a city walk alone. Consequently, to simulate realistic environments, it is necessary to describe and implement small group behaviors such as family connections and friendships. Ultimately, one definitely would be interested in seeing how far one could go by modeling crowds with small groups, instead of modeling every individual in a crowd. The computation time saved would be quite significant.

The foregoing suggests an interesting research opportunity to experimentally measure and then model both individual and small group behavior as a means to producing much more realistic, experimentally derived, and statistically valid crowd models. Specifically, future extensions of our work would attempt to identify the degree to which individuals, small subgroups, or large groups of people in crowds must be modeled to create valid models of crowd behavior, as opposed to using models that describe a crowd as one coherent and collective unit, or as the emergent product of the collective behavior of individuals, each reacting completely independently.

One such approach to extend our current work would be to use the framework for describing crowds by Musse et al. (1998). Under this framework, future models would allow us to experimentally manipulate one or several of the following:

- Whether an individual is part of a small group
- The group's size (3, 5, or 9 individuals)
- The group's predefined objectives and path
- Each individual's level of relationship with other crowd members
- The seeking and flocking laws for each individual.

A second potential extension of our current work would be to study the catalyst(s) which would cause observers to change into participants. This approach would go beyond the description of individuals and crowds in terms of individual movement patterns, and instead identifies to what degree the movement patterns of individuals are part of an intentional whole. The distinction between observer and crowd participant is important to the development of robust models of crowd behavior because it allows us to investigate manipulations influencing decisions associated with increasing levels of participation. Historical crowd events with applicability to our current approach include anti-apartheid protests in South Africa, the Iranian Revolution, the Palestinian Intifada, the Los Angeles race riots of 1965 and 1992, peaceful protests in Eastern Europe at the end of the 1980s, crowd responses to U.S. intervention in Somalia, hooliganism at sports events, anti-Milosevic protests in Serbia, anti-WTO riots, etc. Each of these events could be described along a number of criteria that go beyond the description of crowd composition in terms of age and gender, and of the physical environment. Specifically, additional factors could include, but would not be limited to, crowd size, level of crowd homogeneity with respect to cultural, religious, ethnic, and gender composition, weather and terrain, and (para-) military response to crowd actions. Studying these would allow us to extend movement patterns and to test different approaches for crowd modeling against historical data.

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REFERENCES

Bierlaire, M., G. Antonini, and M. Weber. 2003. Behavioral dynamics for pedestrians. In *Moving Through Nets: The Physical and Social Dimensions of Travel*, ed. K. Axhausen, 1-18. Amsterdam: Elsevier.

Helbing, D., I. Farkas, P. Molnar, and T. Vicsek. 2002. Simulation of Pedestrian Crowds in Normal and Evacuation Situations. In *Pedestrian and Evacuation Dynamics*, ed. M. Schreckenberg and S. D. Sharma, 21-58. Berlin: Springer-Verlag.

Helbing, D., P. Molnár, and F. Schweitzer. 1998. Computer Simulations of Pedestrian Dynamics and Trail Formation. In *Evolution of Natural Structures*, *Proceedings of the 3rd International Symposium of the Sonderforschungsbereich 230*, *Stuttgart, 1994*: 229-234.

Intel. 2001. Open Source Computer Vision Library: Reference Manual. Available via <http://www.itee.uq.edu.au/~iris/CVsource/OpenCVreferencemanual.pdf> [accessed February 15, 2006]. (program can be downloaded via <http://sourceforge.net/projects/opencvlibrary/>.

Kendig, T. 2001. Research debunks preconceptions of crowd behavior. Available via <http://www.psu.edu/ur/archives/intercom_2001/May24/weapons.html> [accessed July 16, 2008].

Loscos, C., D. Marchal, and A. Meyer. 2003. Intuitive crowd behavior in dense urban environments using local laws. Available via <http://www.cs.ucl.ac.uk/research/vr/Prjects/Create//publications/EGUK2003Final.pdf> [accessed September 1,2004].

Lucas, B. D., and T. Kanade. 1981. An iterative image registration technique with an application to stereo vision. In *Proceedings of Imaging Understanding Workshop*, 121-130. (Also available via <http://www.cse.ucsd.edu/classes/sp02/cse252/lucaskanade81.pdf>.

Mckenzie, F. D., M. D. Petty, P. A. Kruszewski, R. C. Gaskins, Q. H. Nguyen, J. Seevinck, and E. W. Weisel. 2008. Integrating crowd-behavior modeling into military simulation using game technology. *Simulation and. Gaming* 39 (1) : 10-38.

Musse, S. R., C. Babski, T. Capin, and D. Thalmann. 1998. Crowd modelling in collaborative virtual environments. Available via <http://www.epfl.ch/~thalmann/papers.dir/VRST98_crowd.pdf>. (see also <http://infoscience.epfl.ch/record/101529/files/>. [accessed July 16, 2008].

Oleson, R. and D. J. Kaup. 2008. The CROWDSim Modeling Framework and Some Example Cases, (to appear in the proceedings of the 2008 Summer Computer Simulation Conference (08SCSC), June 16-19, Edinburgh, Scotland) Available via <http://www.simbios.ist.ucf.edu/Research/DynamicHumanBehaviors/Repository/tabid/392/Default.aspx>.

Ulicny, B. and D. Thalmann. 2001. Crowd simulation for interactive virtual environments and VR training systems. In *Proceedings of the Eurographics Workshop on Animation and Simulation '01*, 163-170, Berlin: Springer-Verlag.

Varner, D., S. D. Royse, J. Micheletti, and G. Apicella. 1998. USMC small unit leader non-lethals trainer (SULNT). In *Proceedings of the International Training Equipment Conference (ITEC 98)*. Available via <http://www.tss.swri.edu/pub/1998ITEC_T033.htm>. (see also <http://www.simsysinc.com/itec98.htm>.

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