Fuzzy Logic Control for Gaze-Guided Personal Assistance Robots

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***Abstract*—As longer lifespans become the norm and modern healthcare allows individuals to live more functional lives despite physical disabilities, there is an increasing need for personal assistance robots. One of the barriers to this shift in healthcare technology is the ability of the human operator to communicate his/her intent to the robot. In this paper, a method of interpreting eye gaze data using fuzzy logic for robot control is presented. Simulation results indicate that the fuzzy logic controller can successfully infer operator intent, modulate speed and direction accordingly, and avoid obstacles in a target following task relevant to personal assistance robots.**

Keywords—gaze tracking; fuzzy logic; autonomous robot; obstacle avoidance; personal assistance robot

I. Introduction

With lifespans increasing worldwide due to advancements in healthcare and related technologies, the importance of care for the elderly and disabled is increasing. In particular, there is a shifting emphasis in technology development towards improving quality of life in the face of diminishing physical capabilities. One of the burgeoning areas of this trend is personal assistance robotics. In a typical scenario, a robot assistant may be present in the home to help with basic day-to-day tasks (e.g., object retrieval), especially those tasks requiring navigation throughout the home, since age- or disability-related mobility limitations may keep an individual from performing all these tasks personally. In extreme circumstances, it can even be challenging to give instructions to the robotic assistant, as in the case where the individual is not physically able to type, speak, or otherwise provide clear inputs to the human-robot interface. Here, we present preliminary progress designing a robotic assistance system which relies on gaze tracking, including eye blinking patterns, to infer a person's intent and thereby create instructions for the robot. In this paper, we specifically focus on the intelligent inference of intent based on gaze and blinking input.

This problem is an extension of the task of robotic target following and path planning. Significant work has been done in this area of service robotics, where a robot is to follow a moving target. For instance, some have used computer vision, using optical flow algorithms to track the target [1][2]. Other computer vision-based approaches have used Kalman filters for improving the accuracy of tracking [3]. Other tracking methods include the use of depth images with verification via a state vector machine [4], or following acoustic stimuli [5]. Control approaches in these target-following scenarios include potential field mapping [6] and a variety of other techniques. Of particular interest are fuzzy logic controllers [5][7][8], which tend to be used primarily for steering. Here, we will describe a fuzzy logic controller which not only determines the robot's heading based on the location of the target, but also avoids obstacles and modulates speed based on the perception of intent from the combined gaze direction and blink frequency inputs. This is conceptually based in part on recent work demonstrating how such a combined input using operator gaze could be used for automatic control of endoscope positioning in surgical tasks [9] using a commercially available eye tracking system, which is also similar to the work described in [10]. This approach extends beyond the most typical uses of eye gaze, which tend to be for two-dimensional human-computer interfaces [11].

The remainder of this paper is organized as follows. In section II, the eye gaze data and the fuzzy logic controller are described. In section III, simulation results are presented. Section IV includes conclusions and recommendations for future work.

II. Methods

A. Test Dataset and Simulation

A gaze dataset was artificially generated to have spatiotemporal characteristics similar to those described in [9], in a planar workspace. The data were arbitrarily assumed to be sampled at 10 Hz and included a logical *blink* data channel in addition to the *x* and *y* gaze target channels on the interval [-0.5 0.5], providing a total of over 23 seconds of simulated robot tracking. Due to the noisy nature of gaze data, the target *X* was determined by a linear weighted average of the previous *n* data points *P*, with *n* = 20:

$$X_k = \frac{2}{n}\sum_{i=k-n}^{k}\left(1-\frac{k-i}{n}\right)P_i. \qquad (1)$$

In this particular dataset, there are five intended target locations, characterized by dwelling gaze and higher blink frequency, and it is assumed that a supplementary action such as object placement or retrieval would follow target acquisition (although this supplementary action is beyond the scope of this preliminary study). Within the workspace, three round obstacles were defined to test the ability of the simulated robot

 ISBN: 978-1-61208-352-0

to avoid obstacles while seeking a target. The data were imported into MATLAB (The MathWorks, Natick, MA) for simulation of gaze-based robotic target tracking.

B. Fuzzy Logic Controller

A Mamdani-type fuzzy logic controller [12] with five inputs and three outputs was created using the Fuzzy Logic Toolbox in MATLAB; the Mamdani-type model handles multi-input, multi-output problems better than the Sugeno-type alternative. The inputs, shown in Table I, were intended to take into account the distance to the target, the degree of uncertainty of the target's position, and the presence of obstacles in the path from the robot's position to the target. The outputs, also shown in Table I, were used to control the speed and heading of the robot, including steering adjustments for obstacle avoidance. All of the membership functions were triangular, as shown in Fig. 1.

TABLE I. FUZZY CONTROLLER VARIABLES AND THEIR TRIANGLUAR MEMBERSHIP FUNCTIONS EXPRESSED IN MODAL FORM [LOWER BOUND, MODE, UPPER BOUND]

Input/ Output	**Variables**		
	Name	***Units***	***Membership Functions***
I	Target Δx	distance	negative [-1, -0.5, 0] zero [-0.1, 0, 0.1] positive [0, 0.5, 1]
I	Target Δy	distance	negative [-1, -0.5, 0] zero [-0.1, 0, 0.1] positive [0, 0.5, 1]
I	Target variability	distance	zero [-0.1, 0, 0.1] low [0.05, 0.25, 0.45] high [0.35, 1, 1.4]
I	Blink frequency (normalized)	-	zero [-0.4, 0, 0.4] low [0.1, 0.5, 0.9] high [0.6, 1, 1.4]
I	Obstacle distance	distance	zero [-0.2, 0, 0.2] low [0, 0.3, 0.6] high [0.35, 1, 1.4]
O	Speed	distance/ time	zero [-0.4, 0, 0.4] low [0.1, 0.5, 0.9] high [0.6, 1, 1.4]
O	Heading	rad	up [0.125, 0.25, 0.375] up/right [0, 0.125, 0.25] right [-0.125, 0, 0.125] down/right [0.75, 0.875, 1] down [0.625, 0.75, 0.875] down/left [0.5, 0.625, 0.75] left [0.375, 0.5, 0.625] up/left [0.25, 0.375, 0.5]
O	Heading adjustment	rad	zero [-0.4, 0, 0.4] low [0.1, 0.5, 0.9] high [0.6, 1, 1.4]

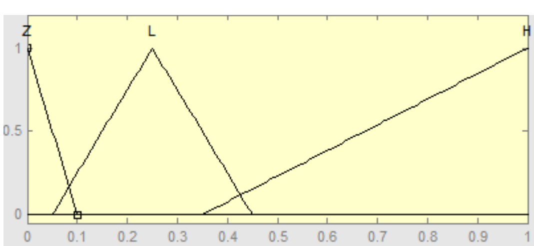

Fig. 1. Membership functions for target variability (zero, low, and high).

The target was determined using a weighted average of the gaze data as in (1), the target and obstacle distance variables were then calculated using the Pythagorean theorem, and target variability was represented by the standard deviation of the gaze input data over the averaging window. Blink frequency was normalized to the interval [0 1] by assuming that four blink events within the 20-sample averaging window was high (achieving a value of 1), and lower blinking rates in the same window of time receive a proportionally smaller membership value. If no obstacles were detected in the direct path between the robot and target, the obstacle distance was set to its maximum value of 1.

Concerning the output variables, the maximum speed was constrained to a value of 0.25 (covering one-fourth the workspace in one second at maximum speed), and the maximum heading adjustment for obstacle avoidance was set at ±100°. The heading variable was scaled to allow the robot to steer within the full 360° range.

Fifteen rules were defined to characterize the influence of the five input variables on the three outputs. In particular, four rules capture the influence of the inputs on the output variable *speed*, eight rules accommodate the division of heading into eight regions in polar coordinates, and the remaining three rules govern obstacle avoidance. The rules defining the fuzzy logic controller are as follows:

1. IF *blink* IS *high* THEN *speed* IS *high*
2. IF *target* Δx IS *positive* OR *target* Δx IS *negative* OR *target* Δy IS *positive* OR *target* Δy IS *negative* THEN *speed* IS *high*
3. IF *target* Δx IS *zero* AND *target* Δy IS *zero* THEN *speed* IS *zero*
4. IF *target variability* IS *high* OR *blink* IS *low* THEN *speed* IS *low*
5. IF *target* Δx IS *positive* AND *target* Δy IS *zero* THEN *heading* IS *right*
6. IF *target* Δx IS *positive* AND *target* Δy IS *positive* THEN *heading* IS *up/right*
7. IF *target* Δx IS *positive* AND *target* Δy IS *negative* THEN *heading* IS *down/right*
8. IF *target* Δx IS *negative* AND *target* Δy IS *zero* THEN *heading* IS *left*
9. IF *target* Δx IS *negative* AND *target* Δy IS *positive* THEN *heading* IS *up/left*
10. IF *target* Δx IS *negative* AND *target* Δy IS *negative* THEN *heading* IS *down/left*
11. IF *target* Δx IS *zero* AND *target* Δy IS *positive* THEN *heading* IS *up*
12. IF *target* Δx IS *zero* AND *target* Δy IS *negative* THEN *heading* IS *down*
13. IF *obstacle distance* IS *zero* THEN *heading adjustment* IS *high*

14. IF *obstacle distance* IS *low* THEN *heading adjustment* IS *low*

15. IF *obstacle distance* IS *high* THEN *heading adjustment* IS *zero*

The first four rules govern the robot's speed. Higher blink rates imply a more focused operator intent and cause increased speed (rule 1). Conversely, high gaze variability or low blink rate imply a less sure target and lead to lower speed (rule 4). The higher the distance to the target, the higher the necessary speed to reach it in a timely manner, and speed should drop to zero as the target is reached (rules 2-3). It should be noted that lower speeds are sometimes desirable to conserve energy either when the goal is unclear or has been reached.

Rules 5-12 pertain to heading. These are relatively straightforward and use the four cardinal directions and the four semi-cardinal directions to navigate in the planar map based on the relative target distance in the *x* and *y* directions.

The remaining three rules constitute the robot's obstacle avoidance behavior. The closer the obstacle, the larger the heading adjustment applied to go around it. Whether this adjustment is added or subtracted from the heading variable is determined by whether the obstacle centroid is to the right or the left of the straight line along the robot's heading.

III. RESULTS

Simulation in MATLAB revealed the ability of the fuzzy logic controller to simultaneously determine human intent from the combined gaze location and blink data, use this intent to modulate robot speed, follow a moving target, and avoid obstacles. In Fig. 2, it can be observed that the robot (whose position is indicated by red diamond markers) can start at a location somewhat removed from the initial target, quickly acquire the target, and then follow it consistently without colliding with obstacles in the workspace.

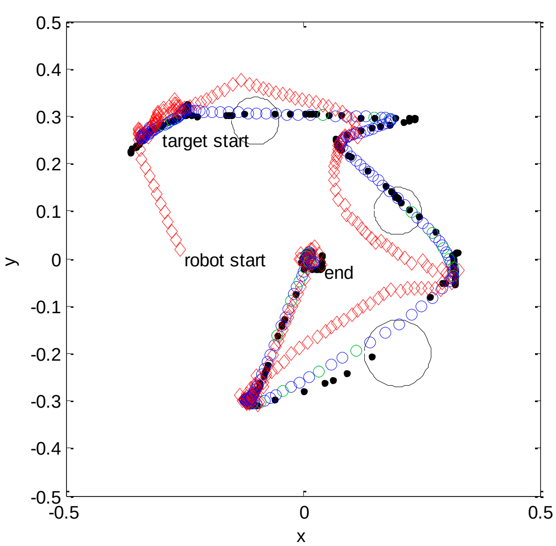

Fig. 2. Target following behavior: robot (red diamond markers) follows target (blue circles) while avoiding fixed environmental obstacles. Green circles indicate target location with a *blink* event. Targets of definite interest (based on dwell duration and blink frequency) are at approximately (-0.3, 0.3), (0.1, 0.3), (0.3, 0), (-0.1, -0.3), and (0, 0). Raw gaze data are shown as black dots.

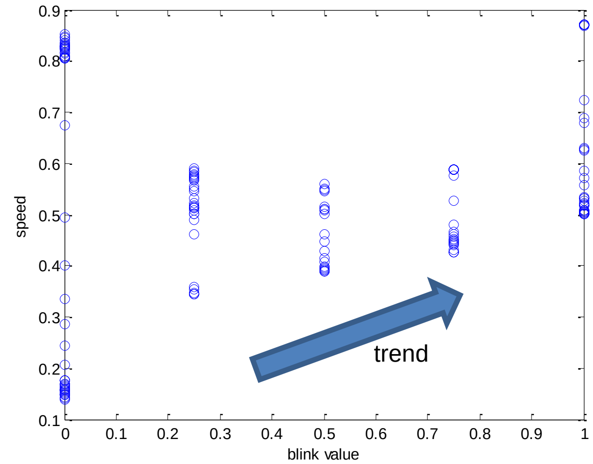

Fig. 3. Output speed as a function of *blink* membership function value: a positive correlation is noted.

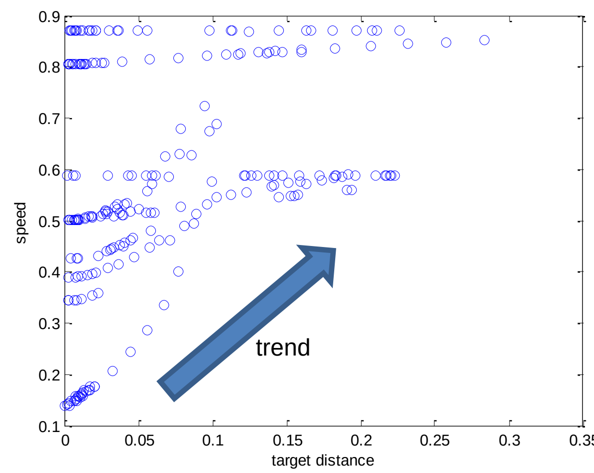

Fig. 4. Output speed as a function of target distance: a positive correlation is noted.

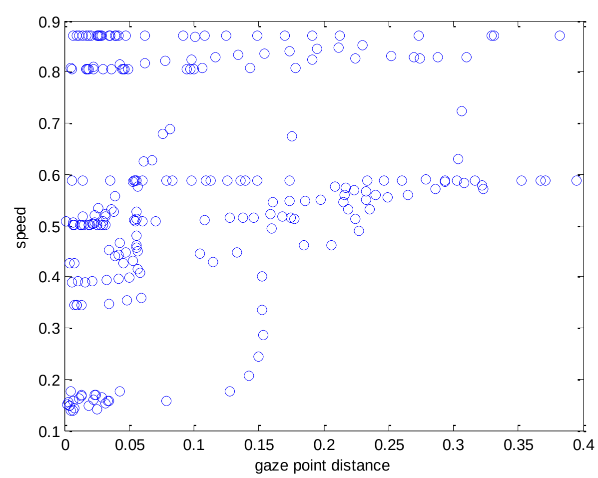

Fig. 5. Output speed as a function of distance to current gaze location: correlation is much less pronounced.

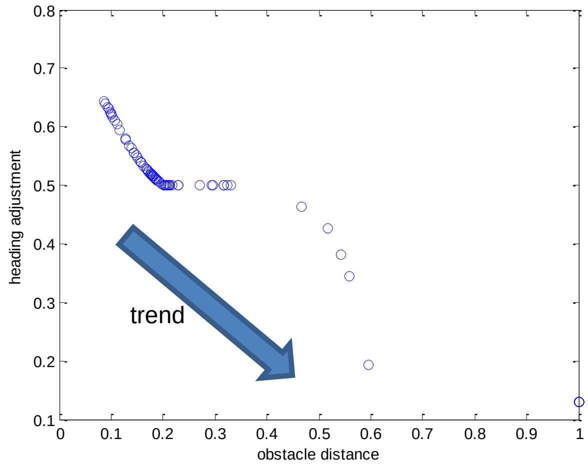

Fig. 6. Modulation of heading adjustment based on obstacle distance demonstrates effective obstacle avoidance.

The more interesting outcomes of the simulation are highlighted in Figs. 3-6. In Fig. 3, one can see that robot speed tends to increase with blink frequency, as intended. High speed at low blink can be attributed to the effects of target distance (particularly at the beginning of the simulation). Note that the results in Fig. 3 are striated at discrete levels, since blinking is a discrete, logical event; this could be smoothed by applying an averaging method similar to that used in target determination. Target distance also has an important effect on speed, as shown in Fig. 4. In contrast, Fig. 5 illustrates that the relationship between robot speed and distance from the robot to the actual gaze point is less pronounced, since the target is based on a weighted average of the gaze point and is thus a less noisy signal. The interdependence of speed on multiple input parameters is evident in Figs. 3 and 4. The effectiveness of the obstacle avoidance behavior is shown in Fig. 6 by the clean heading adjustment curve.

IV. CONCLUSIONS

In this paper, a new technique for gaze-based guidance of personal assistance robots has been illustrated. Fuzzy logic allows the robot to simultaneously manage multiple behaviors, practicing energy conservation when appropriate but pursuing the target when human intent to do so is clear. Combined use of the eye gaze point and blinking data is a pivotal feature of the fuzzy logic controller. Basic obstacle avoidance is demonstrated as an integrated behavior within this controller.

The preliminary results presented in this paper suggest promise for additional future work. The fuzzy controller should be tested using actual gaze data acquired from human users using an eye tracking system, with and without a real-time robot presence, to determine how visual feedback between the robot and human may affect human gaze input. The controller should also be tuned for improved performance, and some of its more basic rules may be replaced by a more sophisticated steering and obstacle avoidance rule set. More advanced work will focus on detailed implementation for a broader variety of personal assistance tasks (e.g., object pick-and-place, operating on a static object) in a true 3D environment.

ACKNOWLEDGMENT

Contributions by X. Zhang to the motivating concept of this paper, and support for this research from US NSF award 1264504, are gratefully acknowledged.

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 ISBN: 978-1-61208-352-0