Application of Control Theory Principles to Human Movement to Ensure the Safe Operation of Robots

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***Abstract*—As robotic systems enter our workplaces, roads, and homes, it is becoming increasingly important to ensure that robots are able to work safely and effectively with and around humans. Understanding the ways in which humans move in their environment and communicating this understanding to robotic systems can allow robots to operate safely and productively around humans. This project uses empirical data to gain understanding of the regularities in human movement and to find motion laws that reflect the movement of humans in cluttered environments. The data collected through this project supports the idea that human walking patterns exhibit a power law relationship between the speed and curvature of human feet (Eq. 1), regardless of the trajectory of motion. This project considers both a single human walking in set patterns and around obstacles and two humans walking in a shared, and perhaps cluttered, space (Fig. 1, 2). For a single person walking through various patterns and around obstacles, the exponent of the power law averaged at -0.8089 (Table I). For two people walking in a shared space while performing avoidance maneuvers, the exponent averaged at -0.7713 (Table I). Future work aims to further analyze human walking patterns around obstacles and other humans, as well as walking patterns around robots. With a better understanding of these walking patterns, planning algorithms can leverage the steering laws used by humans to better control the behavior of robots that operate in the same environment as people.**

I. Introduction

Human-robot interaction (HRI) is governed by the understanding, design, and evaluation of robotic systems that work with and around humans. As the capabilities of robotic systems have expanded, interaction between humans and robots has increased [1]. Improving this interaction is critical to develop service robots that can perform tasks in numerous nonindustrial settings. This will allow robots to work with and benefit non-expert users in homes, hospitals, schools, urban areas, and various other domains. Advancements in HRI technology can lead to the success of health-care robots that may improve patient care, search and rescue robots that may benefit disaster victims and rescue workers, robotic teacher aides that could assist students academically, and several other types of interactive robots that can greatly benefit people [2].

In order to develop robots that can interact successfully with humans, additional research needs to be conducted in the field of human-robot interaction (HRI). In order for interactive robots to be successful, they must be able to operate alongside humans in a way that is robust, reliable, and safe. This requires motion planning and control strategies that ensure the safety of all humans in the shared space. A critical component of HRI is the ability of robotic systems to monitor humans in their environment to ensure the actions of the robot are safe [3]. By using physiological signals from the humans, robots can gain information about the humans' reactions to the robots' actions and predict the humans' movements [3]. One of the greatest challenges surrounding HRI is the need for robots to reliably identify and track human partners and to effectively model the behavior of humans [2]. If a robotic system is able to monitor humans and interpret their physiological signals appropriately, it will be better prepared to develop pre-collision strategies to ensure that the robot does not collide with a human.

II. Problem Formulation

A. Human Collision Avoidance Behavior

The first step in enabling robots to monitor and interpret physiological signals from humans is to gain an understanding of natural human behavior. Numerous studies have been conducted to better understand human collision avoidance behavior–a critical component of human movement around robotic systems. Studies derived from fundamental aspects of game theory [4], as well as those that rely heavily on empirical data [5], have helped increase the understanding of how humans interact when around another human.

A critical component to ensuring the robots move in a way that is reliable and socially acceptable is to be aware of the mutual influence between humans and robots in a shared environment. Humans are interaction-aware, meaning that their actions are dependent on the assumptions that they make about other people in their environment. For example, two humans walking toward each other will both likely move slightly to avoid the other and would expect the other person to behave similarly. Rather than focusing on independent motion panning of individuals, it is beneficial to consider the cooperative behavior of humans. One method to consider human motion planning is to approximate the human decision making with the theory of Nash equilibrium in non-cooperative games, where the Nash equilibrium is a best response for all agents [4]. This idea, derived from game theory, was found to be more effective than previous methods in approximating the decision process behind human avoidance behavior [4]. This indicates that it is important to consider interactions between humans, as well as potential interactions between humans and robots, rather than treating humans as independent agents, unaware of those in their environment.

Further work has been done to collect empirical data on the ways in which humans interact with other humans and avoid collisions. The goal of this body of work is to use motion capture data to better understand these interactions and characterize human collision-avoidance behavior. There are various measures to understand avoidance behavior–collaboration, clearance, anticipation, and synchronization. Collaboration indicates the extent to which lateral distance is shared between two people, clearance considers how close two people allow each other to pass, anticipation depends on the spatial relation between deviation actions, and synchronization reflects the temporal relation between deviation moments [5]. The way these measures impact human avoidance behavior are somewhat dependent on the individuals, but they are all significant to collision-avoidance [5]. These measures may be significant to consider in robotic motion planning, as they impact the ways in which humans behave around other humans, the ways they may behave around robotic systems, and the ways they may expect robots to behave around them.

B. Modeling Human Arm Movement

There has also been significant work on characterizing coordinated human arm motion and finding regularities in this movement. One idea to consider is that humans move their hands in a smooth motion. Rather than making sharp, disconnected movements, humans seem to naturally follow smooth trajectories with their hands. Empirical studies have found some truth in this prediction.

In assuming that humans seek to produce the smoothest possible movement with their hands, researchers have considered that human hand motion aims to minimize the square of the magnitude of jerk over the entire movement, which is associated with the smoothness of the motion. Human subjects performing voluntary unconstrained point-to-point movements typically exhibited hand motions that followed a straight path with a bell-shaped tangential velocity [6]. Similarly, when performing unconstrained curved movements around an obstacle, subjects' motions tended to have portions of low and high curvature, where curvature and tangential velocity were found to be inversely related [6]. This is inline with the predictions of a mathematical model whose objective is to minimize the square of the magnitude of the jerk, suggesting that human motions do, in fact, have some relation to jerk and smoothness.

Similar work has been derived from the idea that humans' complex arm movements naturally tend to follow smooth paths. The two-thirds power law was derived mathematically from a smoothness cost function, and was found to be effective in predicting human arm movements in some cases [8]. The two-thirds power law further reflects the inverse relationship between speed and curvature, claiming that

$$v = g\kappa^{-\beta} \tag{1}$$

where v is the velocity of arm movements, κ is the curvature, g is a constant gain factor, and the commonly accepted exponent β is $1/3$. For simple movements, the gain factor is a constant value that produces a single segment on a $log(\kappa)$ vs. $log(v)$ plot. For more complex movements, the gain factor is more often a piece-wise function. There is evidence to suggest the velocity-curvature relation is robust, but the exponent is not necessarily $1/3$ in all cases, and the gain factor may not be a constant value [8]. The power law is also not consistent with all shapes and does not reflect straight-line motion or points of inflection effectively. However, it does present valuable insight into human arm movement and has proven to be effective in characterizing some human arm motions [8].

C. Modeling Human Avoidance Behavior

There is great interest in the area of human-robot interaction (HRI) to understand and model human avoidance behavior as a way to better predict how a human will move in cluttered environments around robots and other humans. With the ability to find regularities in human movement, robots could be better designed to interact with and around humans. With the ability to accurately model human motion patterns, robots could effectively navigate spaces around humans and avoid collision. Human arm movements shows smooth motions that reflect power laws that relate speed and curvature. We seek to extract similar insights into the regularities of human walking patterns. Through analysis of empirical data, we seek to determine the extent to which power laws reflect human avoidance behavior in various scenarios and consider how natural human walking patterns may exhibit other regularities.

III. Experimental Design

A. Equipment & Lab Space

The lab space is equipped with a Vicon motion tracking system, consisting of 14 cameras–2 video cameras and 12 motion capture cameras that record the location and orientation of an object every ten milliseconds. For every desired object, Vicon can determine its x, y, and z coordinate points in millimeters and its heading with respect to the origin in degrees. To track the movement of humans walking in the lab space, participants strap a motion tracking device to each of their shoes. Each device contains markers placed in a unique pattern, which allows Vicon to recognize each shoe as a distinct object. We can then collect data on the coordinates and heading of the feet of participants while walking in the lab.

B. One Person Trials

To better understand the characteristics of human walking behavior and the regularities that govern this movement, we conduct numerous trials with a single participant for four set-ups. Each of these trial types can be seen in Figure 1. In the first three trials types, the participant walks in the lab space following a given shape. In the first trial type, they walk in a circle (Fig. 1a), in the second, they walk in an ellipse (Fig. 1b), and in the third, they walk in a figure eight (Fig. 1c). In each these figures, the green circle indicates where the participant started, the red square indicates where they ended, and the

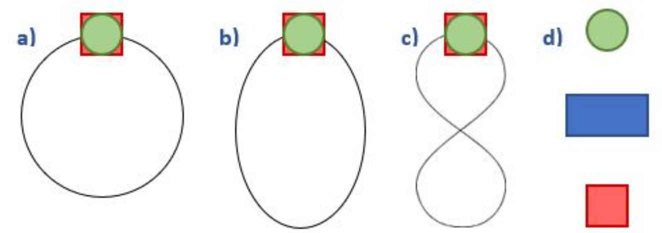

Fig. 1. Various set-ups with one person to understand human walking patterns. a) Participant starts in center of lab and walked in a circle, returning to original point. b) Participant starts in center of lab and walked in an ellipse, returning to original point. c) Participant starts in center of lab and walked in a figure eight shape, returning to original point. d) Participant starts at one end of the lab and walked to the other side, avoiding an obstacle in the middle.

black line indicates the approximate path the participant is expected to follow for a given trial. In the final single-person trial type, the participant walks from one end of the room to the other, avoiding an obstacle in the middle of the room. They started at the green circle in Fig. 1d and walk to the red square, avoiding the blue rectangle in the middle.

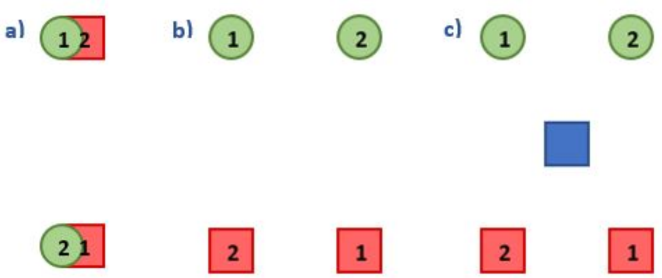

Fig. 2. Various set-ups with two people to understand human avoidance patterns. a) Participants start opposite each other and move across the room, while avoiding each other. b) Participants start apart and move diagonally, while avoiding each other. c) Participants start apart and move diagonally, while avoiding each other and an obstacle.

C. Two Person Trials

To better understand the characteristics of human avoidance behavior, we conduct numerous trials with two participants for three distinct set-ups. Each of these trial types can be seen in Figure 2. In the first set-up, the participants are standing directly across from each other at opposite sides of the room. They must move to the point the other person is standing, while avoiding each other along the way. Fig. 2a depicts two people starting and ending at opposite points in the lab. The green circle with the one indicates where participant one started, and the the red square with the one indicates where participant one finished. Similarly, the starting and ending points of participant two are indicated. In the second set-up, the participants start in two corners of the lab and move diagonally across the room to the opposite corner of the lab, while avoiding each other (Fig. 2b). In the third and final set-up, participants start in two corners of the lab and move diagonally to the opposite corner of the lab, while avoiding each other and an obstacle in the center of the room (Fig. 2c). Each participant is depicted in the figure as before, but there is an additional blue rectangle to indicate an obstacle placed intentionally to interfere with the paths of the participants.

IV. Analysis of Human Avoidance Behavior

A. Data Analysis Procedures

The Vicon system provides us with the coordinate and heading of each foot at various times throughout a trial. Given this information, we aim to relate the speed and curvature of human walking trajectories across various trials for a particular set-up. For a given set-up, we begin by looking at each trial individually, compiling all of the usable data for that trial. While a person is walking, we have data for both of their feet individually, and we calculate the midpoint of the two feet at each point in time. We then approximate velocity and acceleration at each point of time, using the coordinate of the midpoint and knowledge of the frame rate as follows:

$$\begin{aligned} v_x &= \frac{x_2 - x_1}{frame_2 - frame_1} * frame\ rate \\ v_y &= \frac{y_2 - y_1}{frame_2 - frame_1} * frame\ rate \\ v_z &= \frac{z_2 - z_1}{frame_2 - frame_1} * frame\ rate \end{aligned} \tag{2}$$

$$\begin{aligned} a_x &= \frac{v_{x2} - v_{x1}}{frame_2 - frame_1} * frame\ rate \\ a_y &= \frac{v_{y2} - v_{y1}}{frame_2 - frame_1} * frame\ rate \\ a_z &= \frac{v_{z2} - v_{z1}}{frame_2 - frame_1} * frame\ rate \end{aligned} \tag{3}$$

Velocity at a single point in time is represented as $\vec{v} = [v_x \ v_y \ v_z]$, and acceleration at a given point is the vector $\vec{a} = [a_x \ a_y \ a_z]$. We then calculate normalized velocity at each point in time:

$$\vec{T} = \frac{\vec{v}}{\|\vec{v}\|} \tag{4}$$

With this, we can calculate the time derivative of the normalized velocity at each point as follows:

$$\dot{\vec{T}} = \frac{(\vec{a} - (\vec{a} \cdot \vec{T})\vec{T})}{\|\vec{v}\|} \tag{5}$$

Finally, we compute the curvature at each point:

$$\kappa = \frac{\left\|\dot{\vec{T}}\right\|}{\|\vec{v}\|} \tag{6}$$

We now have the speed and curvature for the midpoint of two feet walking in a lab at various points in time for a trial of a particular type. We compute the same values for all twelve trials of that type and compile them all together. We can then compute a log-log plot of speed versus curvature and perform a linear regression to analyze the relationship between speed and curvature for human walking patterns. We perform those same computations for each of the trial types individually and present our results in the following sections.

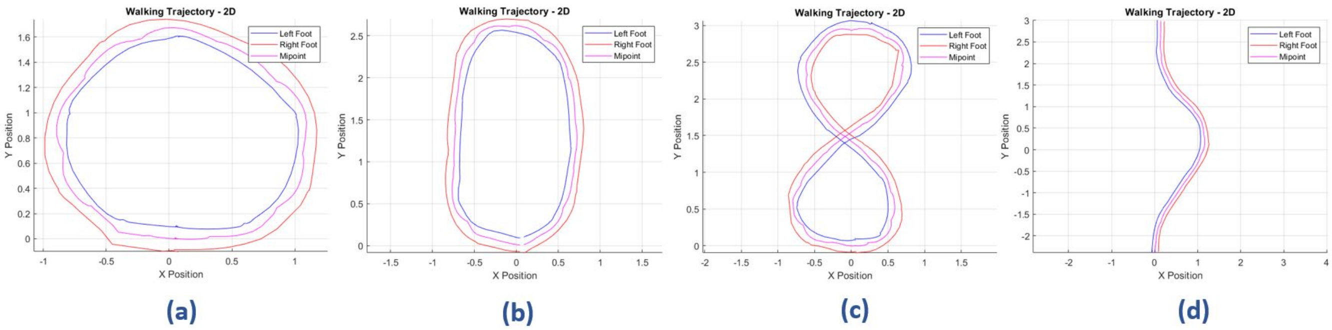

Fig. 3. Trajectories of a sample trial for each single person trial type: a) Circle b) Ellipse c) Figure Eight d) Obstacle

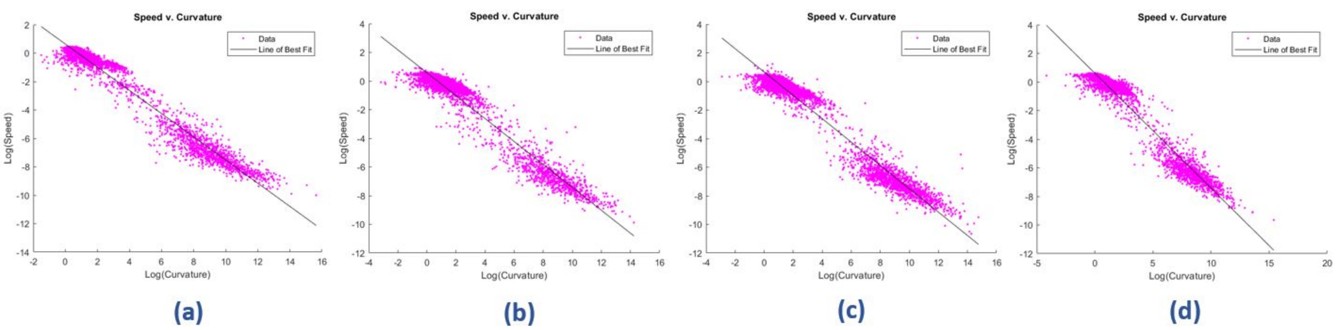

Fig. 4. Curvature versus speed plots for each single person trial type: a) Circle b) Ellipse c) Figure Eight d) Obstacle

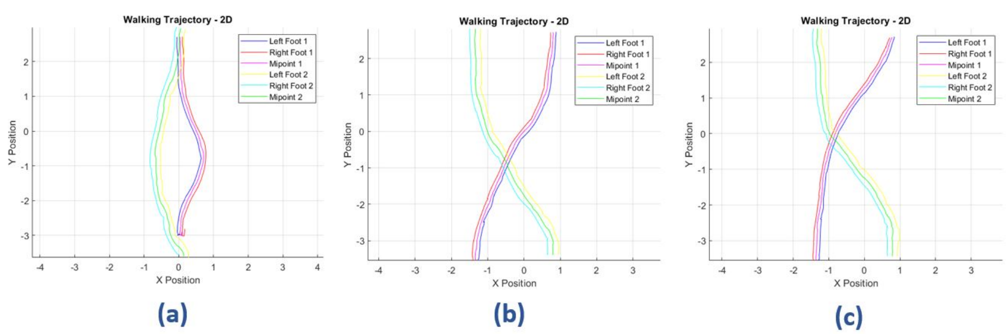

Fig. 5. Trajectories of a sample trial for each two person trial type: a) Opposite b) Diagonal - No Obstacle c) Diagonal - With Obstacle

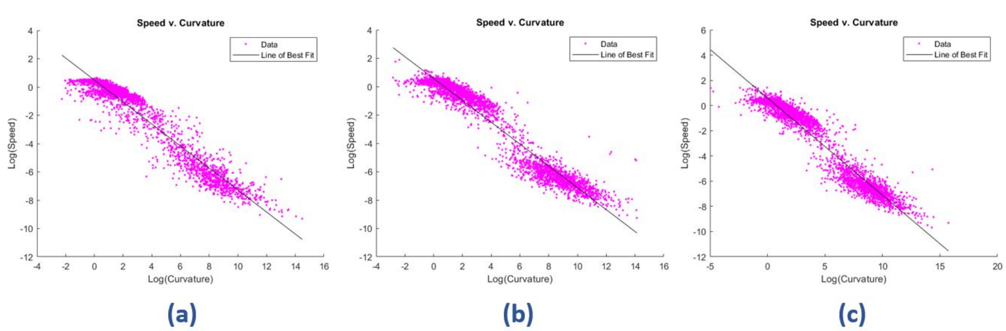

Fig. 6. Curvature versus speed plots for each two person trial type: a) Opposite b) Diagonal - No Obstacle c) Diagonal - With Obstacle

B. One Person Analysis

Beginning with the trajectory data plotted in Fig. 3, which we have for each trial within a given trial type, we compute the speed versus curvature relation depicted in Fig. 4. For each of the trial types, we perform a linear regression on the data and found the slope and y-intercept of the line of best fit, which are displayed Table I. Given this information, we can look at the equations relating speed and curvature for these walking patterns: circle (7), ellipse (8), figure eight (9), and obstacle avoidance (10).

$$\begin{aligned} log(v) &= -0.8154 * log(\kappa) + 0.6349 \\ v &= 4.3142 * \kappa^{-0.8154} \end{aligned} \tag{7}$$

$$\begin{aligned} log(v) &= -0.7998 * log(\kappa) + 0.5763 \\ v &= 3.7696 * \kappa^{-0.7998} \end{aligned} \tag{8}$$

$$\begin{aligned} log(v) &= -0.8170 * log(\kappa) + 0.6599 \\ v &= 4.5698 * \kappa^{-0.8170} \end{aligned} \tag{9}$$

$$\begin{aligned} log(v) &= -0.8034 * log(\kappa) + 0.6096 \\ v &= 4.0701 * \kappa^{-0.8034} \end{aligned} \tag{10}$$

C. Two Person Analysis

Beginning with the trajectory data plotted in Fig. 5, which we have for each trial within a given trial type, we compute the speed versus curvature relation depicted in Fig. 6. For each of the trial types, we perform a linear regression on the data and found the slope and y-intercept of the line of best fit, which are displayed Table I. Given this information, we can look at the equations relating speed and curvature for various walking patterns: participants walking in opposite directions (11), participants crossing paths (12), and participants crossing paths with an obstacle (13).

$$\begin{aligned} log(v) &= -0.7775 * log(\kappa) + 0.4926 \\ v &= 3.1089 * \kappa^{-0.7775} \end{aligned} \tag{11}$$

$$\begin{aligned} log(v) &= -0.7707 * log(\kappa) + 0.5694 \\ v &= 3.7102 * \kappa^{-0.7707} \end{aligned} \tag{12}$$

$$\begin{aligned} log(v) &= -0.7712 * log(\kappa) + 0.5955 \\ v &= 3.9400 * \kappa^{-0.7712} \end{aligned} \tag{13}$$

TABLE I

Walking Power Law Coefficients			
Walking Pattern	Slope	Y-Intercept	R Squared
(1) Circle	-0.8154	0.6349	0.9604
(1) Ellipse	-0.7998	0.5763	0.9416
(1) Figure 8	-0.8170	0.6599	0.9579
(1) Obstacle	-0.8034	0.6096	0.9439
(1) AVERAGE	-0.8089	0.6202	———
(2) Opposite	-0.7775	0.4926	0.9235
(2) Diagonal	-0.7707	0.5694	0.9383
(2) Obstacle	-0.7712	0.5955	0.9357
(2) AVERAGE	-0.7713	0.5525	———

V. Conclusion & Future Work

Based on the results of this study, there is a power law relationship between the speed and curvature of the midpoint of human feet in simple walking patterns. This relationship is given in the following form: $v = g\kappa^{-\beta}$, where v is the velocity of the midpoint of the feet, κ is the curvature, g is a constant gain factor, and β is a constant exponent. For a single human walking in a standard shape (circle, ellipse, figure eight), there is a clear negative linear relationship between the log of the curvature and log of the speed, indicating a power law relationship for these walking patterns (Fig. 3, 4). This same relationship was seen for a single human walking around an obstacle (Fig. 3, 4), as well as two humans walking past each other in opposite directions, two humans walking diagonally across a room, and two humans walking diagonally while avoiding an obstacle (Fig. 5, 6).

Previous work found the velocity-curvature power law relationship to be relatively robust for human arm movements, noting that the generally accepted value of the exponent is $-1/3$ [8]. However, this power law did not always hold true in practice, and the exponent varied in some cases, depending on specific arm motions [8]. We found that the exponent in the power law relationship of human feet varied some for different walking patterns but remained at a relatively constant value across trial types (Table I). For two people walking in various patterns, the exponent remained around -0.7713 with little variation. For a single person walking in various patterns, there was a bit more variation, with the exponent averaging at -0.8089. Note that the exponents we found for human walking patterns varied significantly from the accepted exponent for human arm movements, but the general relationship between speed and curvature of our results is consistent with previous findings.

Future work aims to consider other methods to analyze the walking patterns of two humans in a shared space. Possible future avenues of research would consider ideas from boundary following and control laws exhibited by flocks. There is also great interest in considering the interaction of humans with robotic systems. While it is critical to have a general understanding of how humans move in a cluttered space and how humans move in the presence of other humans, it is important to consider how the typical behavior of humans may vary in the presence of robots. Future work aims to characterize how humans move around robots that are following various planned trajectories. By increasing the understanding of how humans move around stationary objects, other humans, and robots, robotic systems can be better designed to interact safely and effectively with humans.

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