INVISIBLE LEASH: OBJECT-FOLLOWING ROBOT

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Abstract:

This study looked at developing a simple concept for an object-following robot, meant to follow a person in an agricultural setting. A KIPR Link was used as the framework, and simple mathematical relationships were derived to control the motion of the robot. The work described is meant as a proof-of-concept, not as a full-scale development. Reasonable results were obtained, indicating that the robot could successfully follow the object.

Keywords: *object-following, agriculture, KIPR Link, unmaned robot*

1. Introduction

Unmanned robots are of significant interest currently. There is a push from the NSF (National Science Foundation) to accelerate the development of robots that can work beside or cooperatively with people [2]. In the past, several different approaches have been used to achieve unmanned control. These approaches are summarized in the following sections. The goal of this work is to develop a person-following method that will work in many settings, where obstacles and equipment are always changing. Agriculture could use this method to haul equipment around the farm or field while the user is able to use his or her hands for other tasks. Outside of agriculture, this method could also be used for handicapped persons who need help carrying multiple items, such as groceries. Additionally, any manual laborers who have a large amount of equipment to carry around could benefit from this person-following method.

1.1. Path Learning

Path learning has been applied in several techniques. Araujo and Ameida [1] uses a trial-and-error method, with learning, to navigate a path. Spatial resolution is chosen using a game-theoretic cell-splitting criteria. This method is able to avoid obstacles and with each repeat of the same path or environment, its navigation becomes quicker (less learning necessary). This does not fit as a direct solution for the problem, but this method is of particular interest as an addition for future work, allowing a unmanned robot to navigate obstacles while following a person.

1.2. Image-Based Visual Servoing

Multiple projects [3, 7, 8] have used image-based visual servoing, or a modification of the method. This method uses the image Jacobian to determine velocity vectors. It is necessary to know points in the environment in this method, but a modification of the method, Image Based Visual Navigation developed by [7], does not need this information. Instead, motion vectors from consecutive images are obtained, and compared to the desired motion vectors. Both methods are very involved mathematically, but a simpler solution is desired for this application.

1.3. Person Following

Hu et al tracks the size of a human torso, along with a fuzzy PID, in order to follow the human [4]. This method is limited in its ability to keep up with the human, but is able to discern the target human from other humans in the environment and reliably follow the target at slower speeds. If it were not for the limited ability to keep up with a human, this could be a potential method for the application. Future work will involve including additional vision processors.

1.4. Feature-Matching

Geometrical features of strategically placed landmarks (distinct geometric images) with localization and line tracking algorithms are used to navigate indoors in work by Hu et al [9]. The robot from this work can achieve a speed of 18 cm/s and it is able to accurately discern its location from the landmarks.
In order for a robot to follow another robot, geometrical and color-coded patterns can be used, as shown by [6]. Then covariance matching allows the following robot to correctly identify its target robot/pattern. It is not reasonable to place geometric features strategically in an agricultural field, so this method would be less suitable for the desired application.

1.5. Project Objective

This paper will describe a proof of concept for a simple object-following robot, where the object could be carried by or attached to a human. The concept will be referred to as "InviLeash". The feasibility of this concept will be illustrated with preliminary results. As far as the authors are aware, an object-following approach of this simplicity has not been developed yet.

2. Methods

The concept behind InviLeash is straightforward. The robot will follow a single-color ball, using the process illustrated in fig. 1 and described in later sections. Initial calibration requires acquiring an image of the ball at the desired distance and determining the image coordinates of the ball. The desired distance was selected as a reasonable following distance of 45.7 cm. After initial calibration, a loop is iterated, acquiring images, determining the current ball coordinates, comparing to desired, determining direction vector and translating to motor motion.

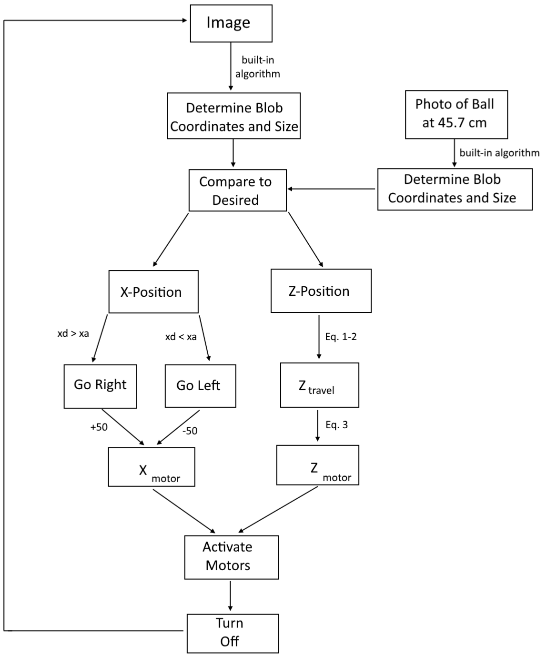

Fig. 1. Concept map for object following

2.1. Proof of Concept

InviLeash uses the KIPR platform from the KISS Institute for Practical Robots [5]. This platform was selected because it has "blob detection" built in, making it ideal for a proof of concept. It also is an open source platform and has a built-in motor-control library. The KISS IDE environment for Windows was used for programming. More information on the KIPR Link and the KISS IDE can be found in the KIPR Link Manual or the KIPR Link C Standard Library (provided with KISS IDE download).

2.2. Design

The KIPR module with USB camera was mounted to a four wheel drive remote control car. The servo motors of the car were controlled by the on-board KIPR motor controllers. Fig. 2 shows the stripped car with module and camera mounted. One motor drives the front axle, another motor drives the rear axle, and a third motor turns the wheels on the front axle.

Fig. 3 shows the direction conventions for the robot, as a top view. Forward is a negative z-value, reverse is positive. A negative x-value is left and right is positive.

A ping-pong ball was used as the ball to follow. In order to avoid confusion with other objects in the vicinity, the ball was painted pink (a distinct and contrasting color not found in the environment). Using the camera channel settings on the KIPR touchscreen, the camera was set to detect the pink color.

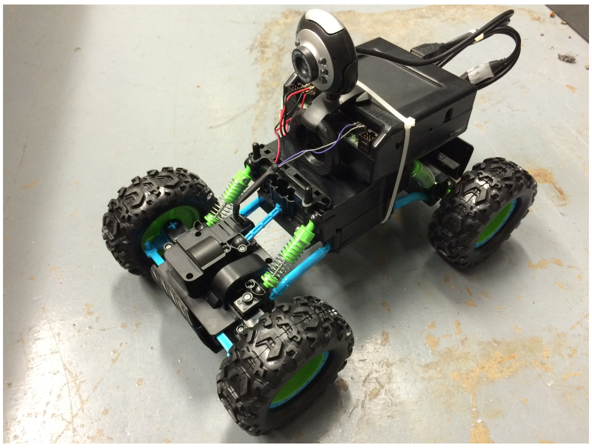

Fig. 2. Object-following robot prototype

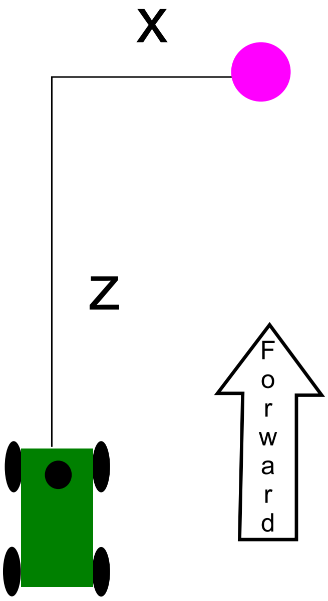

Fig. 3. Direction conventions (top view)

For each image that the camera acquires, a box is identified around the largest "blob" of pink (it is assumed that this is the ball, as there is no other pink in the environment) using the built-in features of the KIPR. The coordinates of the box and the length of the horizontal sides are used to determine the ball's location in the image. Fig. 4 shows the parameters for the desired ball image location (white box) and the actual ball image location (shaded box). It was determined through iteration that the horizontal width of the blob provided more repeatable results than the vertical height of the blob.

Determining Z-Position The z-distance of the ball can be estimated simply using the width of the blob. The relation between z-distance and blob width was calibrated using a second-order polynomial. Fig. 5 shows

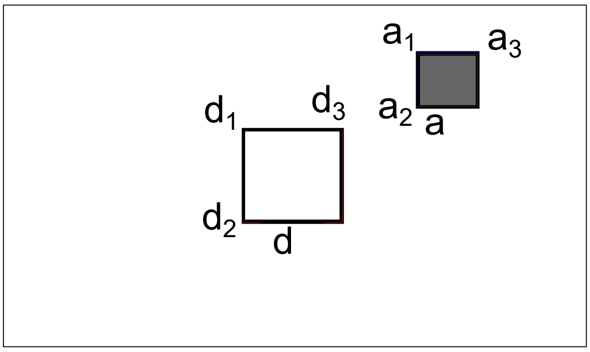

Fig. 4. Size parameters of desired blob (white) and actual blob (shaded)

the results for six trials each at four different ball distances. The resulting calibration equation fit to all 24 data points is

$$z_{dist} = -0.0006a^3 + 0.1009a^2 - 5.6627a + 117.7 \quad (1)$$

where a is the width of the ball in the image, in pixels and z_{dist} is the z-distance of the ball from the robot, in cm. From this, the distance to travel, in cm, can be determined by subtracting the 45.7 cm desired distance. It is likely that the calibration is not linear because of the non-linear optical properties of a camera lens.

$$z_{trav} = z_{dist} - 45.7 \quad (2)$$

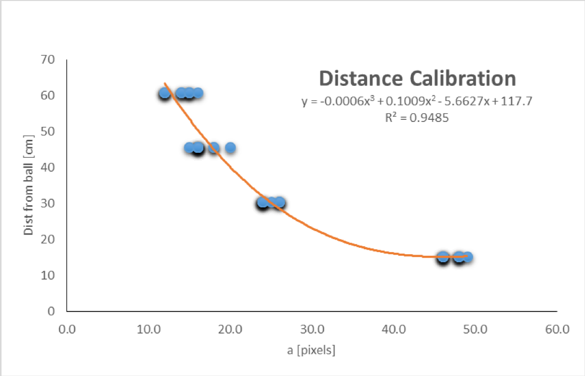

Fig. 5. Calibration of ball distance

Determining Z-Motor Command The servo motor command for z-direction must also be calibrated. The relation between motor command and traveled distance is almost linear, but deviates from linear at the two extremes of distance (near and far). The calibration data is shown in fig. 6, with a linear and a 2nd order polynomial fit. The 2nd order polynomial was selected as a better fit. The equation is

$$z_{motor} = 0.0002(z_{trav})^2 + 0.3208(z_{trav}) - 4.9257 \quad (3)$$

where z_{trav} is the required travel distance in cm, and z_{motor} is the necessary servo motor command (a position between 0 and 2047 ticks) for the required travel distance. For the z-direction motors, a position command of 250 ticks results in 50.8 cm travel distance for the vehicle used here.

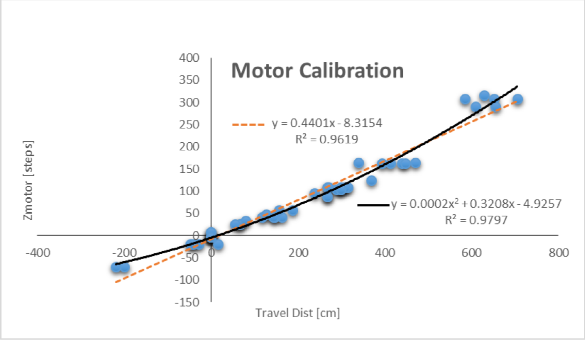

Fig. 6. Calibration of ball distance

Determining X-Position The final calculations are for the x-direction. Using a_1, a_3, d_1, d_3, and blob width, the difference in horizontal center of the blob vs horizontal center of the desired position is calculated, then the y-component of the distance is removed and only the x-component of the distance is considered.

$$x_{dist} = ((a_3 + a_1)/2 - (d_3 + d_1)/2)/(0.03667a + 0.59667) \quad (4)$$

where x_{dist} is the x-component of the distance from actual center to desired center (as described above) and the other parameters are as shown in fig. 4.

Determining X-Motor Command The calibration for the x-direction motor command would depend on how far the x-direction motors would travel, so to simplify this portion of the method a set motor command was used for x-direction. If the robot needs to move right the x-motor command would be +50 ticks, and if the robot needs to move left the x-motor command would be -50 ticks.

Motion Finally, the three motor commands (one for x-direction, two identical for the z-direction) are sent and then the motors are shut off after the commanded positions are reached. From this point, the loop is repeated.

2.3. Results

Overall, the InviLeash had satisfactory performance, considering its limitations (discussed later). The average response and standard deviation from six trials is summarized in tab. 1. It can be noted that as the ball moves further from the camera (in the direction of decreasing desired travel), the standard deviation increases. This is likely related to the image resolution of the system. Fig. 7 and fig. 8 show a visual representation of the results. The average response was promising.

Tab. 1. Actual Travel Results

Desired Travel [in.]	Actual Travel [cm] Avg	StDev
30.5	22.3	3.9
15.2	13.2	1.5
0	-4.2	5.4
-15.2	-11.0	8.8

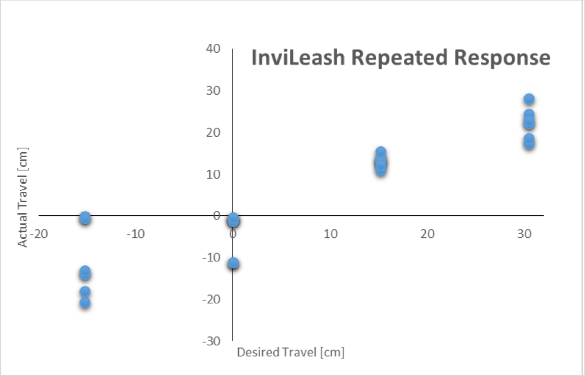

Fig. 7. Repeated Response

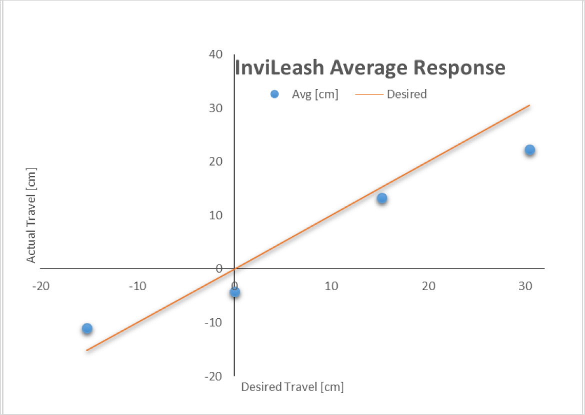

Fig. 8. Average Response

Limitations and Problems The results of the InviLeash were limited by some important factors, summarized in tab. 2. The largest issue was with the limitations in image resolution. Regardless of the camera, the KIPR system has a set resolution of 160x120. This greatly degrades the accuracy of the system. In future work, a different platform will be used, such as openCV, an open source computer vision program.

Tab. 2. Issues with Proof of Concept

Issue	Cause	Solution
Distances are approximate	Limited image resolution on KIPR	Use a different platform, such as openCV
Limited troubleshooting	Small screen on KIPR, no read-out to computer screen	Use a different platform, such as openCV

3. Applications

Future work will focus on applying this technique to agricultural applications, such as a helper robot to follow a worker around with equipment or tools. The robot will incorporate path-learning so that it can also function without user interaction. Obstacle avoidance will also be necessary, as well as rugged terrain navigation ability. This technique could also be used in industrial settings, to tow trailers or to haul pallets around a warehouse.

This platform could link with sensors such as LIDAR for local steering, or could be linked with GPS to supplement or replace navigation information in locations where GPS information is limited. Additionally, it is envisioned that color-lighted wands or balls could be used as the object to follow, so that the robot can distinguish between two different people. Along the same lines, a serial pulse code could be employed.

4. Conclusions

Although this is a very simple platform, the potential for future work is abundant. The initial results were promising regarding the ability to follow an object. There are limitations in the platform, including processing speed which limits the speed of following, and in-consistent identification of the target, but there are plans to minimize the limitations. Employing a different computing platform such as Arduino or LabVIEW myRIO may help improve processing and following speed. Additionally, using a distinct flashing light as the target may help in consistent identification of the target.

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REFERENCES

[1] R. Araujo and A. de Ameida, "Mobile robot path-learning to separate goals on an unknown world". In: *Intelligent Engineering Systems Proceedings*, Budapest, 1997.

[2] N. S. Foundation. "National robotics initiative", 2014.

[3] C. Gao, X. Piao, and W. Tong, "Optimal motion control for ibvs of robot". In: *Proceedings of the 10th World Congress on Intelligent Control and Automation*, Bejing, China, 2012.

[4] C.-H. Hu, X.-D. Ma, and X.-Z. Dai, "Reliable person following approach for mobile robot in indoor environment". In: *Proceedings of the 9th International Conference on MAchine LEarning and Cybernetics*, Boading, 2009.

[5] KISS. "Kiss hardware/software", 2014.

[6] H. J. Min, N. Papanikolopoulos, C. Smith, and V. Morellas, "Feature-based covariance matching for a moving target in multi-robot following". In: *19th Mediterranean Conference on Control and Automation*, Corfu, Greece, 2011.

[7] L. O'Sullivan, P. Corke, and R. Mahony, "Image-based visual navigation for mobile robots". In: *2013 IEEE International Conference on Robotics and Automation*, Karlsruhe, Germany, 2013.

[8] L. Pari, J. Sebastian, A. Traslosheros, and L. Angel, "Image based visual servoing: Estimated image jacobian by using fundametal matrix vs analytic jacobian", *Image Analysis and Recognition*, vol. 5112, 2008, 706–717.

[9] F. Wen, K. Yuan, W. Zou, X. Chai, and R. Zheng, "Visual navigation of an indoor mobile robot based on a novel artificial landmark system". In: *Proceedings of the 2009 IEEE International Conference on Mechantronics and Automation*, Changchun, China, 2009.