ROBOTA Team Description Paper - IEEE Latin American Robotics Competition

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***Abstract*— In this paper we present a general description of our system developed to compete on the OPEN category (*The Bomb Disarming Robot*). To solve the problem, many concepts in Computer Vision, Robotics and Control Systems are explored. Through this paper we will focus on the solutions developed by our team to four distinct issues: The Mechanical Approach, The Vision System, The Navigation System and The Hill Problem.**

I. THE MECHANICAL APPROACH

Thinking about the task proposed, our team considered the bomb disarming a very critical problem, where a simple mistake could cause a lot of loss and damage. Because of this we propose a system composed with two different modules, one called Central Unit, responsible for the main data process and tactical support, and the other called Long Range Mobile Actuator (LRMA), a smart module capable of sensing and actuation with wired connection to Central Unit. Using this approach we can make the main unit be more safe and cheapen the production of the system, besides we could actuate at several targets at same time, simply connecting more LRMA to the system.

A. Central Unit:

The Central Unit is composed with a powerfull CPU, a data connection interface for the LRMAs (we used USB connection) and a simple locomotion system for the support tasks. It also is responsible for all the power supply for the system.

B. Long Range Mobile Actuator(LRMA):

The LRMA is a very versatile module capable to be adapted for many different problems and solutions. We could separate it in three subsystems: locomotion, sensing and actuation. Our LRMAs are, regarding locomotion, a two-wheeled differential-drive system with a fixed standard wheel and modified servomotors. In Sensoring we use a mobile camera, touch sensors and a magnetic compass. The actuation is made by hooks and clamps.

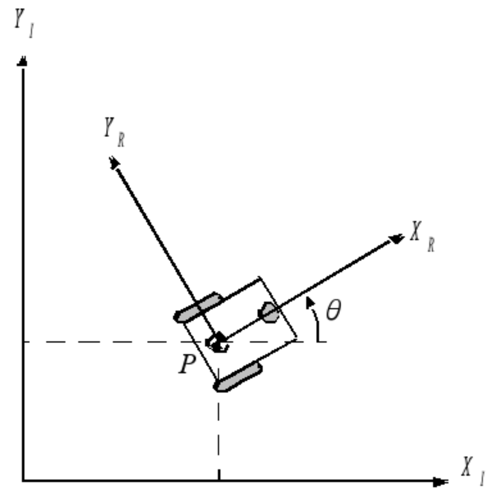

Fig. 1. Differential-drive System

II. THE VISION SYSTEM

Since the Robot must disarm colored bombs pulling colored wires in a given previously defined sequence, our team decided to create our own Image Processing & Computer Vision algorithms. Since the problem is very specific, custom made algorithms would meet our needs best. First, we modeled the Vision System as follows:

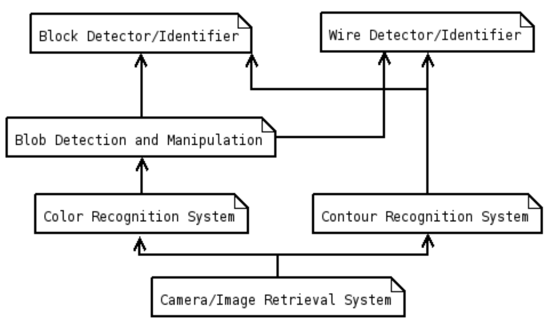

Fig. 2. Vision System

The main goal of the Vision System is to produce, for both *Wires* and *Bombs*, valid (ρ, θ) measurements of position in a polar coordinate system with origin located at the camera's lenses and with $\theta = 0$ at the camera's focal axis. The choice of the polar coordinate system is easily justified

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pointing out that the actuators to be controlled are from a differential drive robot and thus the control system derivation is straightforward.

A. Color Recognition System:

This layer of our system is designed to, given an input image, point the pixels that passes a test we call a "Color Rule". This rules implement both HSV and RGB color spaces segmentation, resulting in improved robustness against ambient light variation.

B. Contour Recognition System:

Since *Bombs* and *Wires* have well defined contours, one could easily find them using well known contour extraction techniques together with a classification algorithm. In our case, feature extraction is done selecting the best candidates after the following criteria:

- $N_{vertices} = 4$
- $\theta_{InternalAngles} \approx \frac{\pi}{2}$
- Polygon's angle to the image reference frame: *Bombs* are always in their stable position

The remaining polygons are passed to the upper layer as measurement *candidates*.

C. Blob Detection and Manipulation:

As a second *feature extraction* technique, we implemented a custom *blob extraction* algorithm that does the following:

- Select the pixels on the input image that correspond to the desired color.
- Filter the selected points cloud using Morphological Image Processing techniques.
- Groups the remaining pixels into *blobs* according to their proximity
- Finds the minimum bounding rectangle (B_{rect}) for each *blob*

After this classification, the *winner blobs* are passed to a upper layer, as measurement *candidates*.

D. Block Detector/Identifier & Wire Detector/Identifier

At this level the features extracted are translated in distance measurements for both *Bombs* and *Wires* in the polar coordinate system. Before actual translation, the measurement candidates are *judged* against rules specific for *Wire* or *Bomb*, some example of rules are:

- Eliminate *Bomb candidates* with $Density(B_{rect})$ smaller than a predefined threshold
- Eliminates *candidates* who's B_{rect} that doesn't conform to
$$\frac{Height}{Width} \approx \begin{cases} 1.0, Bomb \\ 4.0, Wire \end{cases}$$
- Eliminates *candidates* that would result in objects too far ($\rho > 2.5m$) or too close ($\rho < 0.04$) to the camera.
- Eliminates *Wire candidates* that do not lie inside a B_{rect} of the *Bomb* in focus.

Also, a simple Static Kalman Filter, which implements only the *Update* cycle of the Dynamic Kalman Filter (DKF), is used to fuse the information (ρ, θ) gathered by both the Blobs and the Contours methods creating more reliable and robust measurements. Given the measurement γ_1 and γ_2 with its associated σ_{γ_1} σ_{γ_2}

$$\gamma_{final} = \gamma_1 \frac{\sigma_{\gamma_2}^2}{\sigma_{\gamma_1}^2 + \sigma_{\gamma_2}^2} + \gamma_2 \frac{\sigma_{\gamma_1}^2}{\sigma_{\gamma_1}^2 + \sigma_{\gamma_2}^2}$$
$$\sigma_{final} = \sqrt{\frac{\sigma_{\gamma_1}^2 \sigma_{\gamma_2}^2}{\sigma_{\gamma_1}^2 + \sigma_{\gamma_2}^2}}$$

Assuming that both ρ and θ are perturbed by only gaussian noise, measured by extensive sampling, this sensor fusion technique produces the best possible estimative. In our case, a DKF produced bad results mainly for two reasons:

- The competition arena contains highly nonlinear aspects.As examples: wooden cubes can stop the robot from moving, high inclination ramps could make the robot slide down for long distances after a very small robot actuation.
- Uncertainty on the open-loop model of our actuators is much bigger than the ones in our measurements so the DKF would produce, after one *Predict* cycle, almost flat (large σ values) estimations hence not justifying itself.

III. The Navigation System:

A. Outer Control-loop

Given the very specific task in question, our team uses many parallel Finite States Machines (FSM) to implement a Variable Structure Controller such that, for most states, a classical linear control law (PI) is well defined. The remaining states deal with special events such as closing a robot's claw or "blind searches" (the robot, when in a deadlock situation, produces almost-random moves in order to change its position and possibly find a known landmark) [5], [6].

To derive the necessary states and transitions, we developed the model of a *problem solving routine* in a topological manner. Since the competition arena is stationary, we decided upon a Markov Chain to prevent the robot from developing a *stubborn* behavior and thus most state transitions are not absolute [1], [2].

Most transitions are *suggested* by discrete events such as achieving a given control reference or having a bumper pushed.

B. Inner Control-loop

The inner control-loop was designed aiming simplicity, since most of our actuators have bad open-loop models and the feedback-loop is very slow, we use a Proportional-Integrative (PI) controller with variable parameters.

IV. The Hill Problem

The task this year have an elevation with 20 cm height, which must be overcome to achieve the Bomb1, the more usual approach would be suppress the ramp with 28.28 cm length and 45 degrees of inclination. Because of the dimension restriction, the robot will be, in a given time, totally in the ramp, analyzing this with the Newton Laws, decomposing the gravity force we get that the coefficient of friction would be approximately 1, which limits the possibilities for the material of the wheels.

A. Our Approach

To suppress the friction problem our team decide to create a bridge for the LRMA using the Central Unit as the support. The Central Unit has 20 cm height and start with a LRMA over it, and move itself to the corner of the elevation, which allows the LRMA reach Bomb and move more freely over the elevation.

Fig. 3. Concept photo - Central Unit docking

Fig. 4. Concept photo - LRMA over the elevation

V. CONCLUSIONS AND FUTURE WORKS

On extending this project, a better localization method is a good starting point. At a first glance, Monte Carlo Localization (MCL) [2] seems very promising and should solve the neglected problem of the "kidnapped" robot. Another field that deserves improvements is path planning and the control law system. The next step would include research on the implementation of an Extended Kalman Filter (EKF) or even an Unscented Kalman filter (UKF) since they would treat the huge nonlinearities present in both our robot and its environment better. We suggest that the robot could use a mixture of Kalman Filter Localization (KFL) and MCL so that, for an inner and thus faster control loop, it would use predictions generated from KFL and for an outer, slower, control loop it would use predictions from MCL. The actual Computer Vision system is very conservative in order to produce only valid measurements but sometimes it ends up producing no results when some could definetely be produced.

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