LEGS DETECTION USING A LASER RANGE FINDER FOR HUMAN ROBOT INTERACTION

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Abstract: The ability to detect humans is an important skill for service robots, especially if these robots are employed in an environment where human presence is constant, for instance a service robot which works as a receptionist in the hall of a hotel. The principal aim of the proposed method is to estimate the human position using data provided by a Laser Range Finder (LRF). The method utilizes two Finite State Machines (FSMs) to detect some leg patterns and, after that, it computes the probability of being a pair of legs for each detected pattern. In order to validate the proposed method some experiments were performed and are shown.

1 INTRODUCTION

In recent years, great effort has been done in order to improve Human-Robot Interaction (HRI) research field. Researchers such as Bellotto and Hu (Bellotto and Hu, 2009) claim that the studies of HRI are currently some of the most fascinating research field in mobile robotics, and Bekey (Bekey, 2005) emphasizes the idea that cooperation and interaction among men and robots are the big challenges of the next years. Because that, the robots which will interact with humans must have the skill to detect people. This ability will enable robots to understand better and anticipate human intentions and actions (Arras et al., 2007). The main purpose of our work is to develop a laser-based human detection in order to allow a mobile robot to interact with people.

There are many researches concerning people detection using laser scanners. The work done by (Carballo et al., 2009) introduces a method for people detection around a mobile robot using two layers of laser scanners, thus two sets of features for each person are detected. Based on these features and a previous knowledge about human body shape, the human detections is performed. In (Fod et al., 2002), the authors present a technique to track moving objects in a workspace covered by multiple lasers. The method to detect people shown in (Arras et al., 2007), uses a supervised learning technique to create a classifier that facilitates such detection. The classifier is trained using AdaBoost method. A way to detect line and circles from laser data in an indoor environment is introduced by (Xavier et al., 2005). The authors still perform leg detection by considering it as a circle with some particularities like the diameter of the circle. The approach to track multiple moving objects shown in (Schulz et al., 2001) uses laser data and combines particle filters with existing approaches to multi-target tracking. The system uses leg detection and occupancy grids to detect people. Topp and Henrik (Topp and Christensen, 2005) introduces the "Human Augmented Mapping" which represents an integration of automated map generation with learning of environmental concepts. They propose a method similar to the one presented in (Schulz et al., 2001) with the difference that their method allows handling people standing still, which is useful for interaction.

The authors of (Cui et al., 2005) present a system that employs multiple laser scanner and one camera to track multiple persons. They track people through a meanshift method and laser tracking and fuse these two information using a Bayesian formulation. The work presented in (Müller et al., 2007) implements a fusion of laser, sonar and vision data to find and track people by a mobile shopping assistance robot. A system to track people in real time in uncontrolled environments is presented in (Scheutz et al., 2004). This system combines leg detection based on laser data and face detection implemented in the specialized hardware *cellular neural network* (CNN) universal machine. Reference (Bellotto and Hu, 2009) presents a multisensor data fusion techniques for tracking peo-

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ple by a mobile robot using a laser scanner and one monocular camera. They extract the features from a laser scanner and look for some leg patterns. Vision is used for face detection and the human tracking is performed by fusing the two different sensor data. Luo *et al.* (Luo et al., 2007) describe a method to find and track a human using a monocular camera, which is responsible for finding the human face, and a laser scanner assembled on their robot, whose function is to find human body and arms. The data sensor is fused by statistical independence. In (Kleinehagenbrock et al., 2002) a hybrid method for integrating laser range and vision data is presented. They use the laser data to detect human legs and colored images to find skin color and face. These information are fused to better perform the human tracking.

The approach we present in this paper is focused in detecting human legs using a laser scanner and to determine their position. If the legs detection is positive, the robot starts interacting with the human. Our method to detect legs is similar to the approach developed in (Bellotto and Hu, 2009). Their system finds human legs after identifying some legs patterns that correspond to legs apart, forward straddle and legs together. In our case, only two patterns are considered legs apart and legs together. In order to find these two patterns we implemented a Finite State Machine (FSM) and for each pattern found we calculate the probability of being a pair of legs. The advantages of the proposed method are the low computational cost (the implemented method performs each detection in approximately $35ms$), the simplicity (it only uses two FSMs and a probability function to classify a pair of legs) and the low quantity of parameters that need to be estimated (the distance between the legs and the difference between their widths).

The remaining of this paper is organized as follows. Section 2 presents the method to find human legs using a laser scanner. Section 3 illustrates the results of some performed experiments and, at last, the conclusions and future work are presented in Section 4.

2 LEGS DETECTION

The method to detect legs that we are going to present extracts features from a laser scanner and, as the method shown in (Bellotto and Hu, 2009), identifies patterns relative to the legs posture. These patterns correspond to the following situations: legs apart (LA) and two legs together (LT). The structure of the legs detection algorithm can be seen in Figure 1.

In order to determine the most common leg position when a person stops and talks to another, some people were observed. Figure 2 illustrates these situations.

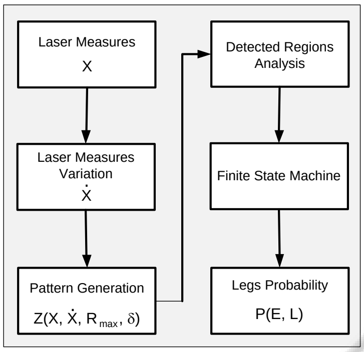
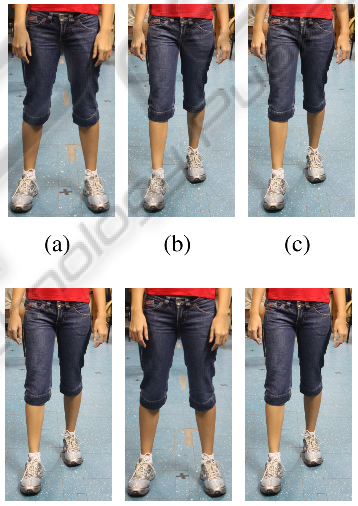


Figure 1: Structure of the proposed algorithm.



(a) (b) (c)

(d) (e) (f)

Figure 2: Legs position. Legs apart (a)-(c). Legs together (d)-(f).

2.1 Transitions Array

The distance measures provided by the laser scanner are stored in an array $X = [x_1, x_2, \ldots, x_N]$ where x_i is each distance measure captured and N is the total number of readings. After that, an array with the difference between two consecutive measures ($\dot{X} = [\dot{x}_1, \dot{x}_2, \ldots, \dot{x}_{N-1}]$) is calculated as $\dot{x}_i = x_{i+1} - x_i$, with $i = 1, 2, \ldots, N-1$. Then, the array $Z = [z_1, z_2, \ldots, z_{N-1}]$, which stores the transitions related with each measure in x_i, is built. Z is created based on X, $\dot{X}$, R_{max} and δ, where R_{max} is the maximum distance we are considering for the measures done by the laser scanner ($2m$ in this case) and δ is a distance threshold. We define five different transitions:

- Transition 0: $|\dot{x}_i| < \delta$ and $x_i = R_{max}$;

- Transition 1: $|\dot{x}_i| > \delta$ and $\dot{x}_i < 0$;
- Transition 2: $|\dot{x}_i| < \delta$ and $x_i \neq R_{max}$;
- Transition 3: $|\dot{x}_i| > \delta$, $\dot{x}_i > 0$ and $x_i \neq R_{max}$;
- Transition 4: $|\dot{x}_i| > \delta$, $\dot{x}_i > 0$ and $x_i = R_{max}$.

Figure 3 illustrates these five transitions. The dashed line indicates the maximum measure, i. e., $2m$.

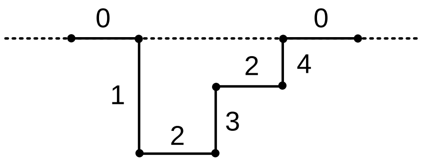


Figure 3: Defined transitions.

2.2 The Finite State Machines

After generating the array Z, it is performed a search for leg candidates (LCs). These candidates are the regions in Z that starts with a Transition 1 preceded by a Transition 0 and finish with a Transition 4. Each can be pre-classified either as single leg or as pair of legs together candidate as follows. A LC is pre-classified as a single leg if the distance between the extremities is in the range $(5cm, 15cm)$. If this distance is bigger than $15cm$ and smaller than $32cm$ the LC is pre-classified as a pair of legs together. Otherwise the LC is discarded.

Once this pre-classification is accomplished, the LCs are verified by two FSMs. One of them looks for the LA pattern and the other for the LT. Each state of these machines receives as input a value between 0 and 4, which represents the transitions already mentioned. A LA pattern is defined as a sequence 012401240 (Figure 4(a)-(c)), where the numbers represent the respective transitions. The LT pattern can assume three different sequences: 0121240, 01240 and 0123240 (Figure 4(d)-(f)).

The patterns shown in Figure 4 correspond to the legs position that appear in Figure 2.

Figures 5 (a) and (b) show, respectively, the FSMs for detecting the LA and LT patterns. To simplify, the inputs that take the FSMs to an invalid state are not drawn in the schematics shown in those figures.

Notice that the numbers close to the arrows that link the states are in the form input/output, where the inputs are the values of the transitions in the vector Z and the output can be either 0 (the pattern was not identified) or 1 (recognized pattern).

2.3 Legs Probability

Once the detected patterns are classified by the FSMs, some characteristics of the pair of legs are extracted

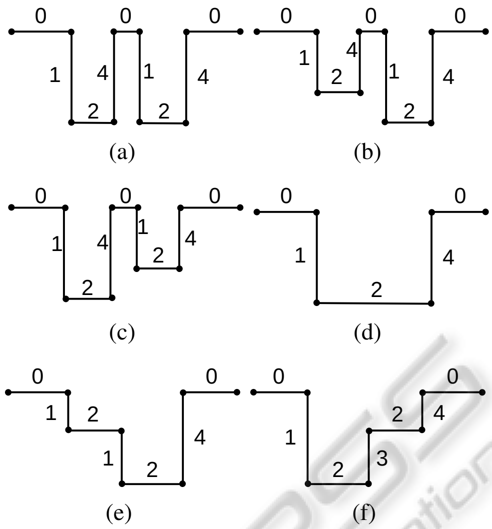


Figure 4: Leg patterns. Legs apart (a)-(c). Legs together (d)-(f).

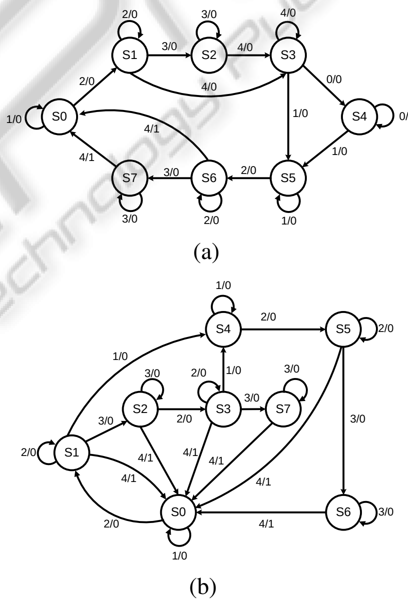


Figure 5: Finite State Machines. Legs apart (a) and legs together (b).

in order to determine a probability of being legs, such as the distance between the extremities (E) and the difference between the width of each detected leg (L). This probability was introduced to avoid situations where, for example, there are two people near the robot, one of them at the left extremity and the other at the right extremity and, moreover, only one leg of each one is detected. In this situation, the FSMs will classify these legs as a pair of separate legs, but since they are far from each other, they have low probability of being a pair of legs which belongs to the same person. Moreover, if a person stands still in front of the robot with legs apart and using a walking stick, it could be interpreted as a leg. However, as the walking stick is thinner than a leg, it will not happen due to the probability of being legs. This probability is calculated as,

$$P(E,L) = \left[1 - \tanh\left((\kappa L)^3\right)\right] \exp\left(-\frac{(E-\bar{E})^2}{2\sigma^2}\right), \quad (1)$$

where L is the difference between the width of each leg, E is the distance of the exterior extremity of two consecutive legs and κ is a positive constant. The average distance of human legs when they stop in front of the laser and the standard deviation are given by $\bar{E}$ and σ, respectively. Figure 6 shows the probability of a pattern to be a pair of legs apart according to variables E and L. For the situation where a pattern is classified as a pair of apart legs by the FSMs, the parameters of Eq. 1 are $\bar{E} = 0.3037$m, $\sigma = 0.028$m, otherwise the values are $\bar{E} = 0.25$m, $\sigma = 0.0268$m. The adopted range for the variable E is $[0.15m,\ 0.45m]$ and for the variable L is $[0,\ 0.1m]$. The value of κ does not change no matter the situation and it is $\kappa = 15$. The graphic of being a pair of legs together is similar to the legs apart and is not shown.

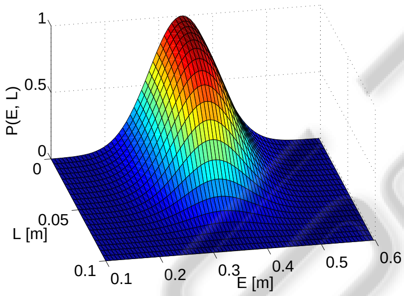


Figure 6: Probability of being a pair of legs apart.

By observing the graphic presented in Figure 6, it can be seen that the probability assumes its maximum value when L is zero and E is equal to $\bar{E}$.

3 EXPERIMENTAL RESULTS

The experiments were performed in an indoor environment using a mobile robot Pioneer 3-AT from ActivMedia, equipped with a laser scanner Sick LMS200. Even though the laser scanner provides distance measures from 0° (right side of the robot) to 180° (left side of the robot), the experiments were performed using the measures from 60° to 120°, because the aim is to detect people who are interested in interacting with the robot. So, people who stop outside the mentioned region, are not considered interested in interacting.

The system was developed in C++ and runs in a PC with MS Windows installed, a Core 2 Duo processor 2.1GHz and 4GB RAM. This PC is capable to execute around 25 loops per second, however we fixed the execution time in 10 loops per second. The robot used to perform experiments is shown in Figure 7.

Figure 7: Robot used to perform the experiments.

In order to show the reliability of the proposed method, some experiments were performed. The robot was positioned in a free area and, while the leg detection algorithm was running, some people were asked to stop in front of the robot in the same manner they would stop when they want to talk to another person and, sometimes, the experiment was performed with more than one person. it were performed 152 detections and the algorithm was able to classify correctly 88.16% of the cases. Figure 8 shows a person stopped in front of the robot and Figure 9 brings the detection rates obtained during this experiment.

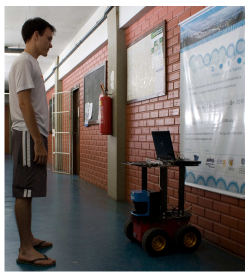


Figure 8: A person stopped in front of the robot.

Before showing the experimental results, it is important to mention that during the tests nobody stopped in front of the robot with the legs together. Due to this, in order to perform a complete set of experimental results, some people were asked to stand in front of the robot with their legs together. Following subsections illustrate some experimental results of the proposed leg detection algorithm.

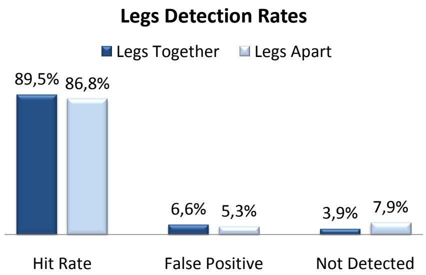


Figure 9: Detection Rates.

3.1 Experiment 01

In this experiment two people were standing still in front of the robot with the legs apart. Figure 10 shows the distances measures captured by the laser scanner and the obtained result for the leg detection algorithm. The circles represent the detected pair of legs by the FSMs, and the numbers represent the probability of being legs of each detected pair of legs.

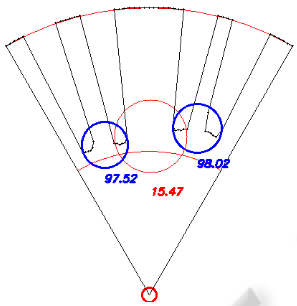


Figure 10: Experiment 01 - obtained results.

Notice that in Figure 10 there are three circles, i. e., the FSMs detected three possible pair of legs apart. However, the second pair of legs detected by the FSMs has a low probability (15.47%) and it is not considered a pair of legs. Moreover the other two pairs have probabilities greater than 97% (see Figure 10) and are classified as a pair of legs. However, if the people were closer one from another, the algorithm would detect three pair of legs instead of two. It can be solved with a face detection algorithm.

3.2 Experiment 02

In this experiment three people stood in front of the robot and one set of measures was captured by the laser. Two of them have the legs apart and the third one has the legs together. The person who is in the middle is the one with the legs together. Figure 11 shows the distance measures captured by the laser scanner and the pattern identification done by the FSMs represented by the circles.

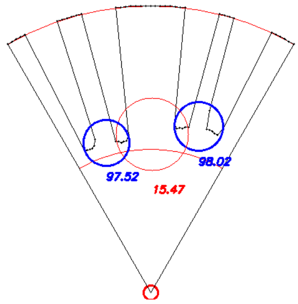


Figure 11: Experiment 02 - obtained results.

The probabilities of being a pair of legs, calculated after the legs pattern identification, are also shown in Figure 11. Notice that all the patterns have a high probability of being a pair of legs, which means that the leg detection algorithm classified correctly the people's legs.

3.3 Experiment 03

As the Experiment 1, this experiment shows the legs detection result for two people stopped in front of the robot. However, here one person has the legs apart and the other one has the legs together. This experiment has the particularity that these two people did not stop in front of the robot with the legs parallel. In this case, as can be seen in Figure 12, one of the legs is closer to the robot.

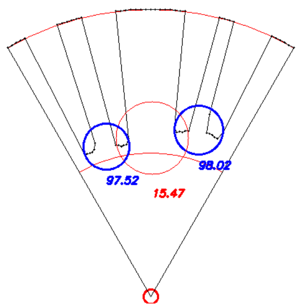


Figure 12: Experiment 03 - obtained results.

For this experiment, the pattern detection by the FSMs and the probabilities of being a pair of legs are shown in Figure 12. Although the legs are not parallel, the algorithm was able do classify correctly the patterns detected by the FSMs.

4 CONCLUSIONS AND FUTURE WORK

We proposed in this paper a method to find human legs using a LRF. The method utilizes the distance measures provided by the laser scanner and look for some legs patterns using two FSMs and, after that, calculates the probability of each detected pattern being a pair of legs.

Some experiments were presented to show the performance of the proposed method. It was demonstrated that the method can detect human legs with accuracy, but since we used only laser sensor information, some false positives can be detected. In order to reduce this false positives and solve occlusion cases, our future work is concerned in introducing a face detection and, thus, performing human-robot interaction.

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