Dutch Nao Team - Team Description for RoboCup 2014 - João Pessoa - Brasil

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Team Description for RoboCup 2014 - João Pessoa, Brasil

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1 Introduction

The Dutch Nao Team consists of students and staff members from three Dutch universities. The Dutch Nao Team debuted in the Standard Platform League (SPL) competition at the German Open 2010. Since their founding the Dutch Nao Team has been qualified for the world-cup competitions in Istanbul, Mexico City and Eindhoven.

Although qualified, the Dutch Nao Team lacks the funding to send its full team to the event, consisting mainly of undergraduate students. Instead the Dutch Nao Team will be present with a small team to participate in the drop-in challenge of the SPL and the technical challenges.

2 Relevant achievements and publications

The Dutch Nao Team is founded in 2010. Since that time, it has participated in several workshops, regional competitions and world cups. When possible, participation in the competition was combined with a symposium publication. In the 2011 World Championships in Istanbul a top 16 position was achieved. At the 2012 World Championships in Mexico the team was eliminated during the intermediate round. In the 2013 World Championships in Eindhoven again a top 16 position was achieved again.

The Dutch Nao Team, and its predecessor the Dutch AIBO Team, has an extensive publication list[4]. The list contains for instance 1 journal article, 3 book chapters, 10 conference papers, 7 master theses and 5 bachelor theses. More details about the current research can be found in section 3.

3 Research

The main focus of the Dutch Nao Team is the combination of Artificial Intelligence and Robotics. The RoboCup initiative gives the team the opportunity to work with various aspects of Robotics.

The team has built their own code from scratch based on Python code. When the limits of this programming language were reached, modules in C++ were created. Integrating these modules inside the NaoTh framework [1] looked possible, yet depended on too many undocumented features. Since late 2013 the Dutch Nao Team has chosen B-Human's code [2] as framework for their code.

[4] See for an overview http://www.dutchnaoteam.nl/index.php/publications/

Its modular design gives the Dutch Nao Team the opportunity to focus on high level programming by giving a more solid low level foundation. With the B-Human framework the team can focus more on bringing the newest AI techniques to the code.

By forking the B-Human framework, we hope to be able to develop modules which will be usable for a large part of the community. The research goals of our group differ from the other teams using the B-Human framework, and we expect to diverge considerable in the future.

Examples of current and future research are presented in the sections 3.1 – 3.8.

3.1 Orientation on the field

The symmetrical field triggered our interest in finding a robust method of overcoming related mistakes in localization. In our recent publication [3], we present an approach to orientate accurately on the field. The visual compass that inspired our approach [4,5] assumes a static environment, infinite distance from the color features, and only a single initialization phase before the actual query phase of the model; assumptions that make this approach weak in dynamic environments such as the one we are interested in.

To overcome these issues, we came up with an extension to the work discussed before [4,5]. To reduce the error that arises by moving from the initialization point, our method [3] constantly builds up a model for several visual compasses, distributed over the field in a grid. Updates can be added even during the query phase, dealing like this with the dynamic environment. The query phase of this model combines information from several cells and features depending on the location and the orientation of the particles from the underlying localization module.

This framework can be extended to a multi-agent setting. Robots can benefit from each other's observations by sharing feature vectors to achieve a faster adaptation to the environment.

3.2 Color-Independent Object Detection

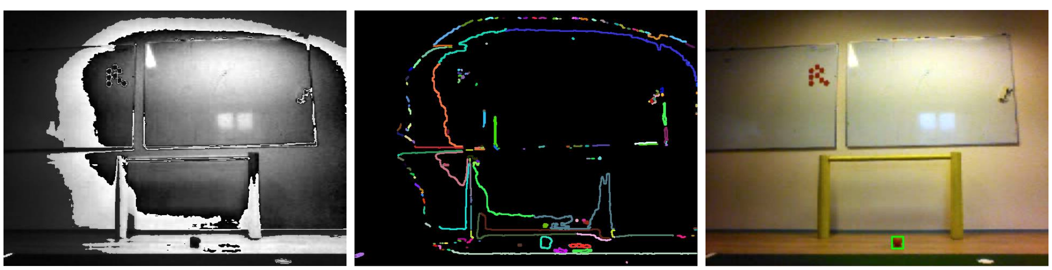
The problem of object detection has been approached in many ways, most of which include searching an image for a particular color. While this has the advantage of being able to quickly determine particular places where the detected object could be, it also has the drawback of color calibration, needing stable lighting conditions and expects the object to be one particular color. The Any Place Challenge (APC) presents us with a number of challenging problems in this area:

1. The unknown field color and unknown background requires an image processing module that can find the relevant objects (the goal and the ball) regardless of the field color and background color, even if there are other yellow/orange/red features present.
2. Since the APC will not take place on a normal SPL field, where the lighting is usually stable, the image processing module needs to be resistant to different lighting conditions.

Our research regarding the APC will mainly be focused on the second point, making a color-independent goal and ball detector, such that even if the ball and/or goal would be a different color (and also the environment) they could still be detected. That means that the image processor does not use the information about the color of the objects to locate them and does not require any calibration. Point 2 will therefore automatically be taken into account, because stable lighting conditions are only required if we wish to do color calibration. And since our image processing module will be independent of color, color calibration will not be necessary. Our approach is split into three parts.

In each time-step, the robot takes a picture and then it goes through the following process:

1. The *pre-processing* step is all about making the edge detection step easy. During pre-processing we split the RGB image into separate red, green and blue channel. The algorithm determines on which channel the objects are most likely to be seen by using the information about the color of the field. This is found by analyzing the histogram of the image for the color that is most present on the bottom half of the image. Then the channel that has the color most opposite of the found color is chosen. After this step, we scale the values of the image such that low pixel values approach 0 and higher pixel values approach a high value, then we normalize the image to get all values back into the RGB range. Right now we have an image where the to be detected objects are well contrasted in comparison to the background.
2. Next, we enter the *edge detection* step. First we smooth the image by applying a Gaussian blur to the processed image. Then the Canny edge detection algorithm is used to find the edges [6]. For the goal, we then use a Hough transform to detect straight lines from the Canny edges that will be associated with the goal posts [7]. For the ball we group together the Canny edges that belong together in the image [8]. We call these the contours.
3. As last we do the *shape-matching and validation.* For the goal, the Hough lines are analyzed to find a set of lines that form the shape of a goal, so a rectangular shape. The ratio of the width to height is used as validation. For the ball, the contours are analyzed to find a shape that is between a circle and a square. This is necessary due to the light spot on the ball and the shadow of the ball. After pre-processing the ball is somewhat of a blob without the shadow and light spot. Then the algorithm validates the found shapes by checking them with the environmental heuristics, such as the positions of the objects.



(a) Image after pre-processing. (b) The detected contours. (c) The detected ball.

Fig. 1: The process for ball detection.

3.3 An effective pushing strategy for Nao

Pushing obstacles is a task that human beings come across quite often. Humanoid Robotics will reach a stage in the future when robots will be executing exploration missions, rescue missions and other types of missions where the task of pushing obstacles will have to be handled efficiently. Hence the objective for the open challenge has been narrowed down to enabling the Nao robot to effectively and if possible, dynamically as well as stably push objects.

Much work has already been done in the field of 'static pushing' using humanoids. The most interesting work in recent literature is the work done on humanoid robot HUBO+ [9]. Different postures that humans use for pushing, namely the feet-together and feet-apart stances (see Fig. 2) were implemented and studied. An articulation in the waist enabled the Zero Moment Point (ZMP) [10] to be moved forward in the pre-pushing stance in both the postures described earlier. This forward movement of ZMP played a crucial role in helping the humanoid robot to exert more force on the object being pushed. But it is understood that usually the feet-apart stance is more advantageous while pushing an object, since the robot would not have to rely on the object for stability. Since the secondary goal is to enable Nao to dynamically push objects, it makes even more sense to work with the feet-apart stance.

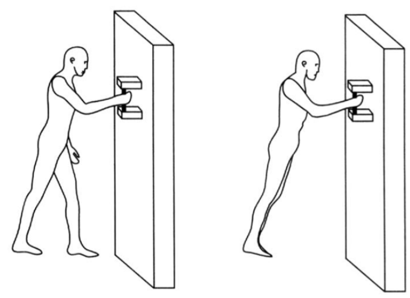


Fig. 2: Human pushing on a fixed handle in a feet-apart posture (left) and feet-together posture (right). Adapted from Rancourt and Hogan [11]

Unlike the HUBO+, the Nao does not have force sensors embedded on its body. Hence, in contrast to the work done on HUBO+, in order to execute the pushing task two controllers that do not require measurement of the reaction force at the hands will be designed.

The purpose of the two controllers is:

1. Controller 1 makes sure that the end effectors of the robot stays in a defined trajectory. The end effectors are the hands and the trajectory can be designed in such a way that the hands mimic the pushing motion that human beings execute. As soon as the end effector comes in contact with an object, there will be a difference between the desired end effector position and the current end effector position, and the controller kicks in. More torque will be exerted and the robot will try to bring its end effector position to the desired position, and as a result the object will be pushed.
2. Controller 2 is mainly used for controlling the position of the center of gravity (CoG). The CoG has to stay within certain bounds in order to ensure stability. In some cases, when the object is too heavy, it might be required that the CoG be displaced ahead so that more force can be exerted. Hence, controller 2 determines the stability as well as the range of force that can be exerted on the object.

3.4 Coach

"*If you play on the ball, you do not have to defend, because there is only one ball.*"

- Johan Cruijff (Dutch coach)

The coach robot of the Dutch Nao Team can choose between three strategies: offensive, defensive and normal. Within these three strategies the individual field players can each perform one of three roles. These roles are: striker, defender and keeper. Each strategy will consist of only one keeper, thus the remaining field players will be divided into the roles: striker and defender. The offensive strategy will consist of four strikers each with a different distance from the ball. The normal strategy will consist of two strikers and two defenders. The defensive strategy will consist of four defenders each arranged with a different position at their teams half. The coach will decide each strategy with different facts about the game which are sent from the gamecontroller.

"*Italians cannot beat you, but you can still lose from them.*"

- Johan Cruijff (Dutch soccer coach)

Also the coach will analyze the strategy of the opponent and will decide the most effective strategy against the opponents strategy. The coach will discover what the strategy of the opponent is by looking at the information sent by the gamecontroller. The strategies proposed in this article will be simulated against each other and will decide which strategy is best against another strategy. The classification of information sent by the gamecontroller within this simulation will assist discovering the strategy of the opponent. Thus the coach will recognize the strategy of the opponent as one of the three strategies described within this section.

"*You only stop learning when you quit.*"

- Ruud Gullit (Dutch soccer coach)

This research will show that the purpose of the coach is effective; however future research can increase this effectiveness. The coach can be updated by a vision part such that it knows the position of the ball and the field players. The coach will decide with this new information more accurate strategies. In previous studies the defenders will intercept more effectively the ball with better interaction; therefore the roles can also be more accurate when updated. The amount of strategies can also be increased, for example one striker, three defenders and one keeper. When there are more roles implemented, the amount of strategies will also increase. The results have shown that a coach is as even important in the standard platform league as it is in the soccer defined by the FIFA. The coach will effectively rearrange the field players which will cause respectively more points in the world cup.

3.5 Emotional players

The intention of this research is to study the potential influence the emotional systems could have on already existing cognitive behavior. To be more specific, this study intends to develop the potential influence of the noise of the public to increase the arousal of the Nao robot, which will influence their soccer behavior of the Nao. There already has been done research towards emotional systems and expressive behavior in Nao robots [12]. However these researches do not go beyond showing the emotion modeled in the Nao robots [13]. They do not influence any cognitive behavior normally exhibited by the Nao robots, for example during a RoboCup match, which they are often used for.

The study starts with implementing an arousal percept within the existing DNT/B-Human Nao framework. The emotional state represented by the arousal model will influence the behavior of the robot. The arousal will be determined by the amplitude of the sounds the crowd makes during a match. The level of arousal will be taken into account when deciding on the parameters of the behaviors the Nao is going to express, for instance by increasing the step-size of the leg or the introducing a swing of the arm. Furthermore, the Nao will be displaying a color when it is responding to the sound of the crowd.

3.6 Player recognition

Recognizing Naos during games has been a longstanding research topic. Most algorithms are computational expensive and lead to a higher overall loss than gaining a tactical advancement.

A technique that only has been used inside the simulation league is using a cascade of weak classifiers to recognize objects. This algorithm is based on Viola and Jones' original algorithm. Not only did the researchers achieve a high performance with this algorithm it is still low in complexity [14] and should be able to run individually on the Naos, which do not have fast processors.

To conduct this research a video dataset will be collected from the Naos gained during football matches played according to the SPL soccer rules. The data will be divided by a training set and a test set and both will be annotated by hand which will be used as ground truth to compare both algorithms on their performance. A boosted cascade of decision trees [14] will be trained using the training set on finding the best selection of weak classifiers to detect Naos. The new algorithm will be tested on the test set and compared to an existing SPL perception algorithm of the same test set. The hope is that we will find a higher performance with the boosted cascade of decision trees than with the current state-of-the-art recognition.

3.7 Sound recognition

In the context of the SPL sound recognition challenge, a system will be built which is able to classify different types of audio signals in real-time. Several techniques will be implemented and their performance evaluated, in order to find the best setup to match challenge requirements.

To achieve reliable signal classification, a fair amount of audio data has to be collected for our learning algorithms. This audio data must include signal audio with the whistle and predefined signals recorded from the Nao's microphones, as well as silent/noise data, and signal data that was recorded in a noisy environment to bolster robustness.

This system will classify audio by analyzing the audio signal from Nao's 4-microphone array using either a fast Fourier transform (FFT) or a discrete wavelet transform (DWT). Some previous attempts at tackling whistle recognition have used FFTs with a single layer perceptron [15] or a rather simple frequency mask [16], yet these studies fail to provide an extensive analysis on performance in noisy environments.

It would be interesting to extend those approaches with more advanced machine learning algorithm. Frequency masks and perceptrons might work well on the first try, but classifier such as the support vector machine, logistic regression, and stochastic gradient descent might handle this task more efficiently. Basically, all we need to know before testing is the input dimensionality they allow. Also, alternative methods for audio analysis, like the DWT, have proven to be a reliable and fast way of extracting temporal and spectral properties of audio for classification [17]. Combining these modules into a interchangeable system will provide us with an easy test setup for both theoretical and real-life testing.

In conclusion, various types of methods for both audio analysis and classification will be implemented, tested, and validated. The most reliable and efficient combination of methods will be used in Brazil for the challenge.

3.8 Drop-in challenge

The drop-in challenge of last year is now scheduled as a full competition. This is a great opportunity to study multi-agent cooperation. During the challenge in Eindhoven, the teams that used static role assignment for the player roles did not perform too well. We intend to assign roles dynamically to our player in the drop-in challenge, as happens as well when playing in the regular league. The roles will dynamically changes depending on the position of other agents and the position of the ball. Furthermore, we will investigate the possibilities to learn more information about the capabilities of our team-mates, for instance with predictive reinforcement learning techniques provided by RRLib[5].

4 Activities

As part of the Intelligent Robotics Lab, the Dutch Nao Team is involved in activities that focus on outreach and on education of both high-school students as well as our own students.

4.1 Demonstrations and media attention

The last year, the Dutch Nao Team has focused on promoting the RoboCup and Artificial Intelligence at several locations in the Netherlands. This was accomplished by giving demonstrations at relevant events and through the use of media[6]. The intention is to give a monthly demonstration of robot soccer is given in the lab for the general public, where changes in code are explained.

4.2 Education and promotion for high-school students

The team is involved in several projects targeting high-school students. For one, the annual summerschool has been transformed into a masterclass. With the support of the Universiteit van Amsterdam, this will be held twice a year. Students will learn the basics of robotics in an assignment to walk through a maze. As a second project, the Universiteit van Amsterdam organizes an annual event where senior high school students study and work on a subject of the bachelor studies of their choice. For the Bachelor in Artificial Intelligence, the practical assignment is to program a Nao to dance, based on a Dutch translation of 'An introduction to robotics with NAO' [18]. As third project, to finish the highest level of high school on a heavily STEM oriented track, a student is creating an interactive version of the assignments in [18].

4.3 Teaching at undergraduate and graduate level

The team has organized a C++ programming course to educate future members and other interested students. This has encouraged freshmen to join the Dutch Nao Team or other teams encompassed by the Intelligent Robotics Lab. By offering projects, students are able to conduct research relevant to the RoboCup for course credits. Workshops and lectures held by peers and local companies are well-attended. Members of the team have attended several RoBOW workshops and the Humanoid Soccer Summer School in Bonn.

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[5] http://web.cs.miami.edu/home/saminda/rllib.html

[6] See for a list of activities http://www.dutchnaoteam.nl/index.php/irobolab/

5 Conclusion

The Dutch Nao Team has become an experienced team. It will continue its research, especially in the field of probabilistic robotics and autonomy. By joining forces with Maastricht University and cooperation with the teams participating in other robotic competitions, it will become possible to apply state-of-the-art techniques in a much broader field than before. It will also continue to educate students interested in robotics, as well as promotion of AI research in general.

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