B-Human

Team Description for RoboCup 2025

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1 Team Information

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1.1 Team Members

Team Leaders: Thomas Röfer, Tim Laue

Students: Adam Cihasev, Liam Hurwitz, Lukas Gittner, Moritz Oppermann, Roman Sablotny, Thade Struckhoff

PhD Students: Arne Hasselbring, Philip Reichenberg

Active Alumni: Ayleen Lührsen, Jo Lienhoop, Jonah Jaeger, Laurens Schiefelbein, Lukas Malte Monnerjahn, Sina Schreiber

2 Code Usage

As of 2017, we used the walking engine of rUNSWift. However, through many iterations of ongoing improvements and adaptions, the engine is replaced with our own version by now. We are currently using the whistle detection released by the team Nao Devils [7]. In the past, we have drawn inspiration from other

Fig. 1. The majority of the current B-Human team members for the RoboCup 2025 season

teams for our own software. One example for that would be the cooling of joints as first presented by the Berlin United. In these cases, only the idea was adopted. The implementation was done entirely by us from scratch.

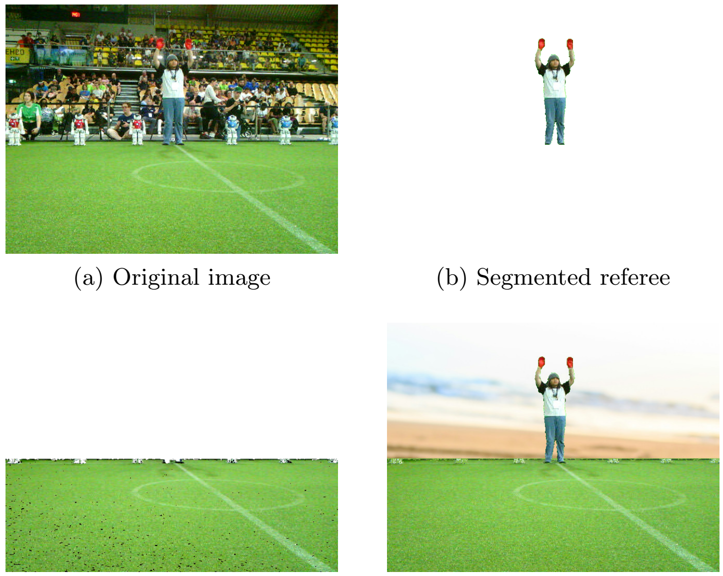
3 Own Contribution

3.1 Recent Contributions

During the last three RoboCup years, B-Human published the following scientific contributions:

– *B-Human 2024 – Enhanced Vision and Faster Ball Handling* (Champion Paper, to appear in 2025) [12]
– *Quantized Neural Networks for Ball Detection on the NAO Robot: An Optimized Implementation* (to appear in 2025) [18]
– *Automated Game Statistics for the RoboCup Standard Platform League* (to appear in 2025) [13]
– *B-Human 2023 – Object and Gesture Detection* (Champion Paper, 2024) [16]
– *Neural Network-based Joint Angle Prediction for the NAO Robot* (2024) [6]
– *Dynamic Joint Control For A Humanoid Walk* (2024) [10]
– *B-Human 2022 – More Team Play with Less Communication* (Champion Paper, 2023) [17]

Details about our released and maintained software contributions are given in Section 5.



(a) Original image (b) Segmented referee

(c) Segmented field (d) Synthetic background

Fig. 2. Synthetic data generation for referee gesture classification

3.2 Contributions for RoboCup 2025

Every year, B-Human makes a variety of changes or new developments in different areas of the code base. This section briefly describes some of our main areas of research and development for 2025.

Detecting Referee Gestures In the past, we only had to detect the referee gesture at the beginning of each half. For this, we relied on Google's MoveNet [20]. Due to a rule change, we now have to detect additional referee gestures during the game to determine which team has a free kick. For example, from the GameController's perspective, when the referee raises their left arm, it indicates that the right team has a free kick.

To achieve this, we are currently working on a new gesture detection. Similar to our previous approach, we extract a small image patch around the referee. However, instead of MoveNet, we are now using our own neural network to directly classify the individual gestures. To further increase the performance of the model, we are training it using data that was synthetically generated.

Synthetic Data Generation For this, we are designing a system to extract images of the referee from logs in order to create a diverse training data set for the referee detection. The primary objective of this system is to achieve high-precision foreground-background separation, enabling the creation of a diverse

Fig. 3. Robot detection and classification of fallen/upright pose

dataset of referee images. By isolating referees from complex and dynamic backgrounds, the system facilitates synthetic data augmentation, which is critical for improving the performance of downstream tasks such as referee gesture classification. The motivation for this work stems from the need to enhance the quality of training data by generating synthetic images where referees are placed in new, controlled environments. This approach involves segmenting the referee and the field from the original image and superimposing them onto a uniform background and placing the segmented referee onto a new background. Examples for these steps are depicted in Fig. 2.

The system employs a multi-stage computational pipeline that integrates state-of-the-art deep learning architectures for semantic segmentation and instance tracking. The process begins with extracting frames from robot log files, followed by initial subject localization using Faster R-CNN with a ResNet50 [11] backbone to detect human bodies and generate anatomical keypoints. These keypoints are then used to initialize semantic segmentation using the Segment Anything Model 2 [9], which propagates annotations across video frames to generate binary segmentation masks. The field segmentation is achieved through a multistep process that combines color-based thresholding and edge detection using OpenCV [5]. Initially, the image is converted to the HSV color space to isolate green regions, which are then thresholded to create a green mask. Simultaneously, the image is converted to grayscale and adaptive thresholding is applied to detect white field lines, followed by morphological operations to refine the edges. These components are combined using bitwise operations to form a comprehensive field mask, which is further refined using horizontal projection analysis to identify and retain only the relevant field area below a detected borderline. The final binary mask is then applied to the original image to segment the field effectively. Finally, advanced masking techniques and edge refinement are applied to isolate the referee and remove the background, ensuring high perceptual integrity.

Robot Detection We use a convolutional neural network (CNN) that predicts bounding boxes around robots and whether they are standing upright or are

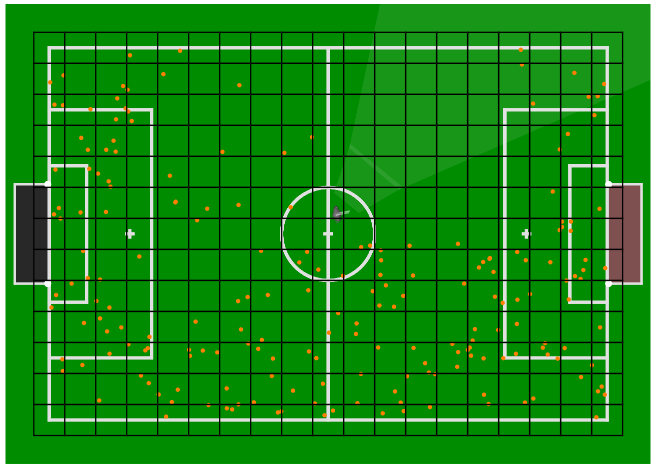


Fig. 4. The new ball search in action. Each orange dot represents a possible ball location. The grid is used to calculate the density of particles.

fallen down. The prediction to which team a robot belongs happens in a separate classification module. To enhance classification accuracy and optimize execution time, we are developing a unified CNN for simultaneous robot detection and jersey classification. This approach enables the exploitation of contextual information within the image, leading to improved performance compared to passing cropped robot images to a separate model. We investigate the efficacy of various network architectures, including a single-scale anchor box architecture (as used in our previous detection network, see Fig. 3), a feature pyramid architecture, and an anchor-free architecture, to determine the most effective design for our application.

Ball Search It is highly important to know the location of the ball at all times. Therefore, if the ball has not been seen by any team member for some time, the ball search behavior gets activated to find it as soon as possible. Previously, this ball search was implemented using a grid of cells that contained the timestamps of the last time the robot looked at the respective cell. The robot then looked at the cell the observation of which was the longest ago. The new approach uses particles instead. Each particle represents a possible ball position as seen in Fig. 4. The robot calculates the area with the highest density of particles by counting the particles inside the cells of a grid. The cell with the highest number of particles is the most likely one to contain the ball and therefore gets looked at first. Normally, the particles are randomly distributed on the field, but if an educated guess about the ball's position can be made, the particles are placed accordingly. An example for this is a corner kick, where all particles can be placed in the corners of the field.

Automated Testing With a team size of seven players, adequately evaluating different tactics, formations, or set pieces becomes a complex process that can hardly be carried out with real robots, if one strives for a high number of samples. Thus, testing in a simulated environment is a common practice. To structure this process, i. e. to automatically carry out a high number of games or game situations with a configurable variance, we are currently adding functionality for automated testing to our simulation. This includes the execution and statistical evaluation of entire halves as well as of configurable situations with a desired outcome. A typical example for the latter would be the execution of a corner kick with the requirement to get the ball into the opponent goal within 45 seconds. For such situations, a flexible description mechanism is currently under development.

4 Unpublished Results

B-Human has participated in the Standard Platform League using the NAO platform since 2009. Since 2020, B-Human has participated in the GORE 2021, RoboCup 2021, GORE 2022, RoboCup 2022, GORE 2023, RoboCup 2023, German Open 2024, and RoboCup 2024 and became the overall winner in each of these competitions. Except for the GORE 2021, which was not an official RoboCup event, these results are all linked on the SPL website.

We will participate in the RoboCup German Open 2025 in Nürnberg, Germany.

5 Impact

Since 2009, B-Human has released most of its code each year after the RoboCup [15]. At least 35 teams based their works on our framework or used at least parts of the code we provided. Our GitHub repository [3] currently has 130 forks. Our library for efficient inference of neural networks *CompiledNN* [19] is used by several teams. Our robotics simulator *SimRobot* [8] has been used by others even if they did not use our software framework. We also released our behavior description language *CABSL* [14], which has again been used by others, even if they did not use our base system.

Since 2009, team members of B-Human have published more than 30 reviewed papers directly related to RoboCup, including two that won a best paper award and four that became best paper award finalists.

Since 2012, B-Human has developed and maintained the league's referee application *GameController*. The latest version for 2023 has been rewritten from scratch in Rust. Over the years, many additional applications were added, such as the *GameStateVisualizer* and the *TeamCommunicationMonitor*. Another part of the package is a tool to export statistics from the GameController's log files, which is the basis for game statistics that we have published for each RoboCup and all local European competitions since 2013. To simplify testing our contribution to the 2022 video analysis challenge [1], we prepared and continue to update an easy-to-use index [2] for the GameController logs, the team communication logs, and the game videos of the RoboCups since 2018.

Furthermore, the B-Human team also has a significant educational impact. The majority of the team members are always students who participate in an official project course. For obtaining a degree at the University of Bremen's computer science department, students have to take such a project course, which is, by the way, heavily weighted in the final grade. We have been running RoboCup-related project courses consistently since the year 2000. Since our start in the current SPL in 2009, more than 160 students participated and learned about many different aspects of robotics. Following the course, many students write their thesis about a B-Human-related topic. To date, 46 theses have been written [4] and a few more are in progress. Many of the aforementioned publications have their origin in one of these theses and build a bridge between education and research.

6 Summary

The RoboCup team B-Human is a joint project of the University of Bremen and the German Research Center for Artificial Intelligence, which has been very successful in the past. The team members are constantly working on the codebase, improving it, renewing it, and adapting it to the rule changes. This year, our focus is on making our behavior strategy more flexible given different field situations and on improving our current implementations, primarily the detection modules. The B-Human team has released a lot of code that is used by others and published several scientific papers over the years. It is also an important educational project at the University of Bremen, in which many students took part over the years.

References

1. B-Human: B-Human's video analysis app, https://github.com/bhuman/VideoAnalysis
2. B-Human: Information about games in the RoboCup Standard Platform League, https://github.com/bhuman/SPLGames
3. B-Human: The official B-Human code releases, https://github.com/bhuman/BHumanCodeRelease
4. B-Human: Theses, https://www.b-human.de/theses-en.html
5. Culjak, I., Abram, D., Pribanic, T., Dzapo, H., Cifrek, M.: A brief introduction to OpenCV. In: 2012 Proceedings of the 35th International Convention MIPRO. pp. 1725–1730 (2012)
6. Fiedler, J., Laue, T.: Neural network-based joint angle prediction for the nao robot. In: Buche, C., Rossi, A., Simões, M., Visser, U. (eds.) RoboCup 2023: Robot World Cup XXVI. Lecture Notes in Artificial Intelligence, vol. 14140. Springer (2024)
7. Kleingarn, D., Brämer, D.: Neural network and prior knowledge ensemble for whistle recognition. In: Buche, C., Rossi, A., Simões, M., Visser, U. (eds.) RoboCup 2023: Robot World Cup XXVI. Lecture Notes in Artificial Intelligence, vol. 14140. Springer (2024)

8. Laue, T., Röfer, T.: SimRobot – development and applications. In: Amor, H.B., Boedecker, J., Obst, O. (eds.) The Universe of RoboCup Simulators – Implementations, Challenges and Strategies for Collaboration. Workshop Proceedings of the International Conference on Simulation, Modeling and Programming for Autonomous Robots (SIMPAR 2008). Venice, Italy (2008)
9. Ravi, N., Gabeur, V., Hu, Y.T., Hu, R., Ryali, C., Ma, T., Khedr, H., Rädle, R., Rolland, C., Gustafson, L., Mintun, E., Pan, J., Alwala, K.V., Carion, N., Wu, C.Y., Girshick, R., Dollár, P., Feichtenhofer, C.: SAM 2: Segment anything in images and videos (2024), https://arxiv.org/abs/2408.00714
10. Reichenberg, P., Röfer, T.: Dynamic joint control for a humanoid walk. In: Buche, C., Rossi, A., Simões, M., Visser, U. (eds.) RoboCup 2023: Robot World Cup XXVI. Lecture Notes in Artificial Intelligence, vol. 14140. Springer (2024)
11. Ren, S., He, K., Girshick, R., Sun, J.: Faster R-CNN: Towards real-time object detection with region proposal networks (2016), https://arxiv.org/abs/1506.01497
12. Röfer, T., Laue, T., Reichenberg, P., Gittner, L., Schiefelbein, L.: B-Human 2024 – enhanced vision and faster ball handling. In: RoboCup 2024: Robot World Cup XXVII. Lecture Notes in Artificial Intelligence, Springer (to appear)
13. Röfer, T., Müller-Groh, L., Hasselbring, A., Laue, T.: Automated game statistics for the RoboCup Standard Platform League. In: RoboCup 2024: Robot World Cup XXVII. Lecture Notes in Artificial Intelligence, Springer (to appear)
14. Röfer, T.: CABSL – C-based agent behavior specification language. In: RoboCup 2017: Robot World Cup XXI. Lecture Notes in Artificial Intelligence, vol. 11175, pp. 135–142. Springer (2018)
15. Röfer, T., Laue, T.: On B-Human's code releases in the Standard Platform League – software architecture and impact. In: Behnke, S., Veloso, M., Visser, A., Xiong, R. (eds.) RoboCup 2013: Robot World Cup XVII. Lecture Notes in Artificial Intelligence, vol. 8371, pp. 648–655. Springer (2014)
16. Röfer, T., Laue, T., Hasselbring, A., Böse, F., Monnerjahn, L.M., van Lessen, K.: B-Human 2023 – object and gesture detection. In: Buche, C., Rossi, A., Simões, M., Visser, U. (eds.) RoboCup 2023: Robot World Cup XXVI. Lecture Notes in Artificial Intelligence, vol. 14140. Springer (2024)
17. Röfer, T., Laue, T., Hasselbring, A., Lienhoop, J., Meinken, Y., Reichenberg, P.: B-Human 2022 – more team play with less communication. In: Eguchi, A., Lau, N., Paetzel-Prüsmann, M., Wanichanon, T. (eds.) RoboCup 2022: Robot World Cup XXV. Lecture Notes in Artificial Intelligence, vol. 13561, pp. 287–299. Springer (2023)
18. Thielke, F.: Quantized neural networks for ball detection on the NAO robot: An optimized implementation. In: RoboCup 2024: Robot World Cup XXVII. Lecture Notes in Artificial Intelligence, Springer (to appear)
19. Thielke, F., Hasselbring, A.: A JIT compiler for neural network inference. In: Chalup, S., Niemueller, T., Suthakorn, J., Williams, M.A. (eds.) RoboCup 2019: Robot World Cup XXIII. Lecture Notes in Artificial Intelligence, vol. 11531, pp. 448–456. Springer (2019)
20. Votel, R., Li, N.: Next-generation pose detection with MoveNet and TensorFlow.js. https://blog.tensorflow.org/2021/05/next-generation-pose-detection-with-movenet-and-tensorflowjs.html (2021)