The Sweaty 2020 RoboCup Humanoid Global System Description*

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1 Walking

Sweaty is able to walk omnidirectionally with arbitrary direction and step size. Motion is produced by a *Motion Generator* with stored motion primitives for walking and kicking. Step size and direction is controlled by an input speed vector. This vector is confined to limit the change of speed and direction per step. Each motion primitive has base points for the basic movement, i.e. lifting the leg and shifting the CoM. Addtionally there are base points for lateral movement, longitudinal movement and rotational movement. These base points are multiplied with the speed vector and superimposed to the basic movement. Splines are used to interpolate between base points. Step interval and target joint angles are adjusted by control algorithms based on CoM position and IMU data.

2 Vision

The Vision is based on our single Fully Convolutional Neural Network called *SweatyNet* [1], [2]. Its Architecture is illustrated in Figure 1. *SweatyNet* uses a Encoder-Decoder design. The encoder has 12 Convolutional and 4 Max-Pooling layers, the decoder has two Upsampling and 6 Convolutional Layers of which two are convolutions with 1x1 filter kernels that reduce dimensionality. We discriminate between the following object classes: ball, goal post, crossing lines, penalty mark, corners of lines, T-junctions of lines, opponents, and obstacles. Each output channel represents an object class. The number of objects per class in an Image is arbitrary. The teaching-signal/ouput is a gaussian distribution around the center of the object.

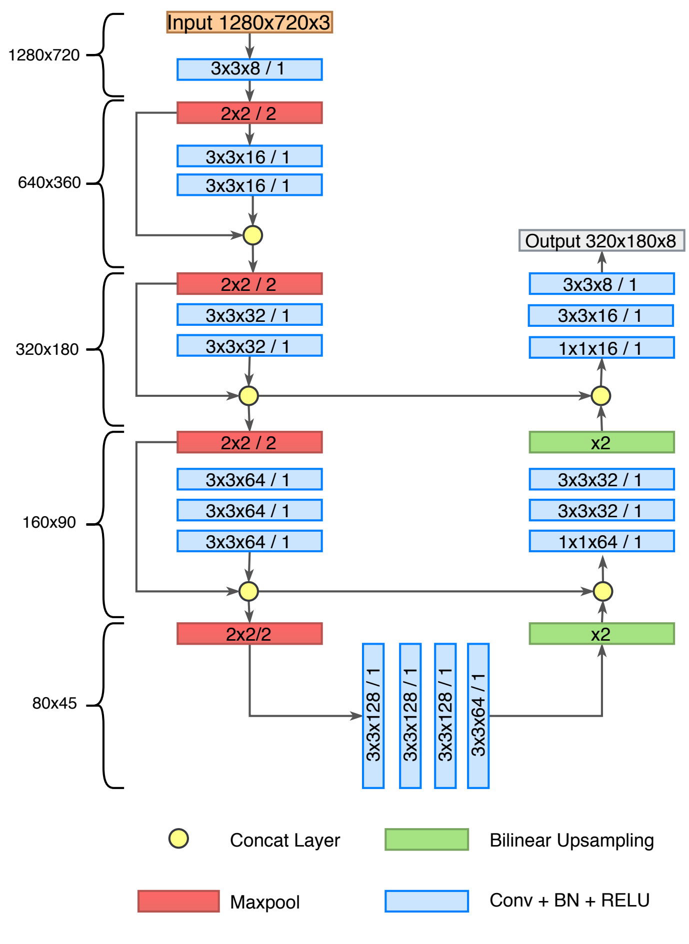

Fig. 1. SweatyNet Architecture

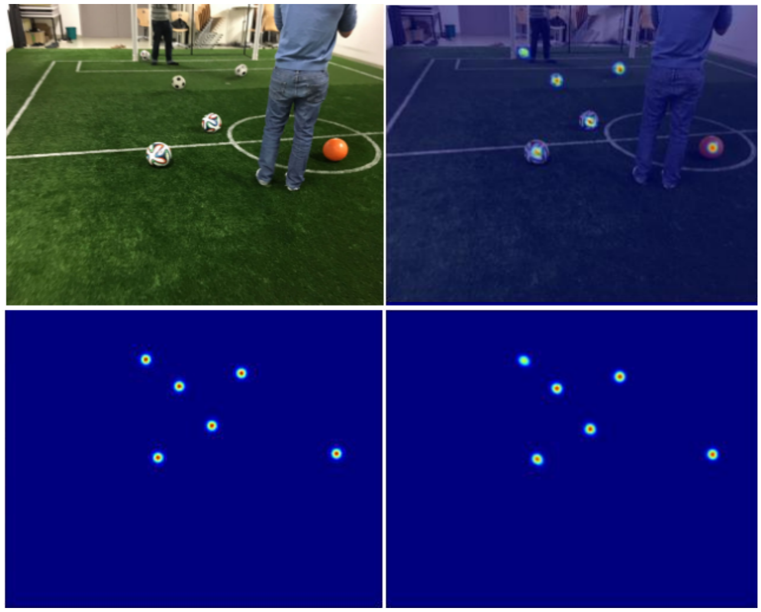

Fig. 2. Teaching Signal and Output

3 Localization

The localization of Sweaty is based on four information sources: inertial measurement unit (IMU), visual feature detections, the kinematic model of the robot and odometry from the walk engine. The orientation of the camera in three-dimensional space is provided by the IMU. This orientation is used in combination with the joint angle measurements and the kinematic model of the robot to determine the height of the camera above ground. In addition to that, odometry information from the walk engine is constantly used to predict horizontal movements. Incoming visual feature detections are assigned depth information by calculating the intersection point of the ray corresponding to the respective pixel with the ground plane. The tree-dimensional visual feature detections are then transformed into the map using the previous localized position and assigned to known features in the environment based on their relative distance. After that, the localization problem breaks down to a 2D localization problem with known point correspondences. IMU z-axis drift is compensated whenever the robot detects two goal posts in an appropriate distance.

4 Behavior

Sweatys' decision process is structured in a directed graph, similar to a tree where branches are allowed to interconnect. The root node consists of a domain specific high level decision maker, e.g. for playing soccer. The branches or intermediate nodes in the graph, referred to as *behaviors*, encapsulate task specific decisions, e.g. walk to position x, y. Low level skills like walking, kicking, etc. correspond to leaf nodes.

In each cycle, the decision graph is reevaluated resulting in an intended execution branch of the graph. In the case that the intended execution branch results in the same low level skill as the currently active execution branch, the intended execution branch is directly taken over and activated. If, however, the intended execution branch results in a different low level skill, it is only activated if the currently active low level skill allows a transition to the intended low level skill. After a decision is made, the active behavior chain is executed.

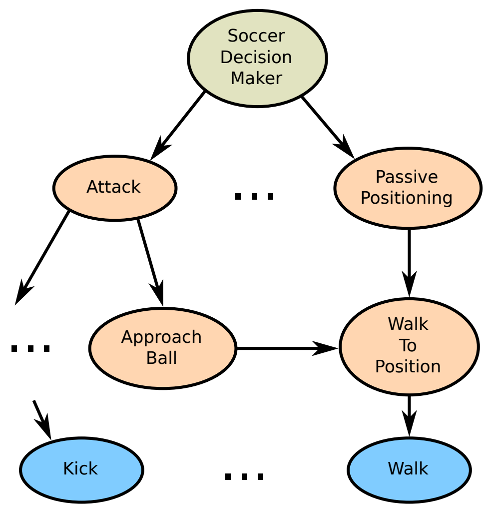

Fig. 3. Exemplary decision graph as used by the Sweaty robot.

5 ROS2 Structure

The new software design in ROS2 is depicted in Figure 4. Similar to the previous design, all hardware components are incorporated into the ROS2 ecosystem via their corresponding drivers. Apart from that, the major components are:

- **SweatyVision**
  This node detects visual features in an image - not changed.
- **Ray-DepthEsimator**
  This node estimates the depth of a feature detection by intersecting the ray corresponding to the detection with the ground plane.
- **PC-DepthEsimator**
  This node uses the point cloud of the ZED camera to assign depth information to feature detections.
- **Magma**
  The decision node - not changed.
- **WalkEngine**
  This node represents the central motion generation and control module.
- **HeadMover**
  This node provides motion generation and control for the head.
- **MotorMapper**
  This node transforms motor positions into joint angles and vice versa.
- **JointInterceptor**
  This node may override certain joint angle measurements based on alternative sensor information.
- **GameControllerROS-Bridge**
  This node provides the connection to the game controller.
- **Mi-Te-Com ROS-Bridge**
  This node incorporates the MiTeCom team communication protocol into the ROS2 ecosystem.

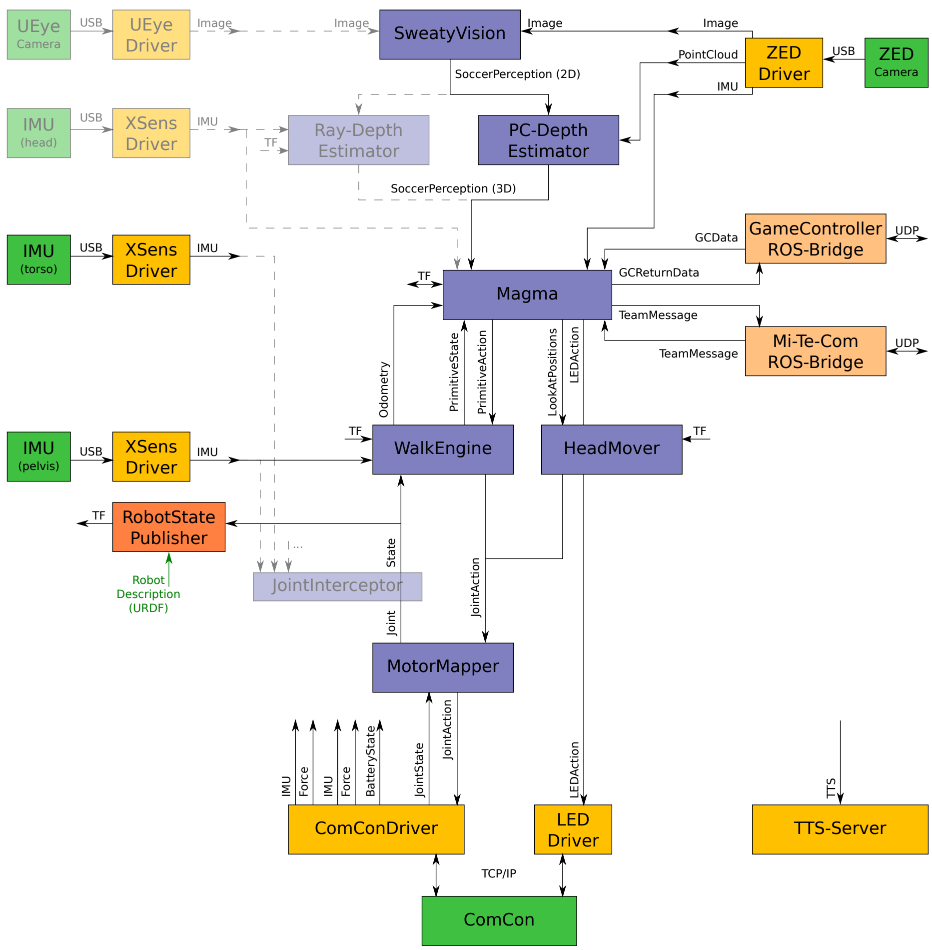

Fig. 4. Nodes and exchanged messages in ROS2.

Table 1. The dynamic coordinate system frame descriptions and its publisher.

Child Frame ID	Parent Frame ID	Publisher Node
/torso_base	/pelvis	RobotStatePublisher
/torso_intercon	/torso_base	RobotStatePublisher
/torso	/torso_intercon	RobotStatePublisher
/neck	/torso	RobotStatePublisher
/head	/neck	RobotStatePublisher
/l_shoulder	/torso	RobotStatePublisher
/l_upper_arm	/l_shoulder	RobotStatePublisher
/l_upper_elbow	/l_upper_arm	RobotStatePublisher
/l_lower_elbow	/l_upper_elbow	RobotStatePublisher
/l_lower_arm	/l_lower_elbow	RobotStatePublisher
/l_hip_intercon	/pelvis	RobotStatePublisher
/l_hip	/l_hip_intercon	RobotStatePublisher
/l_thigh	/l_hip	RobotStatePublisher
/l_shank	/l_thigh	RobotStatePublisher
/l_ankle	/l_shank	RobotStatePublisher
/l_foot	/l_ankle	RobotStatePublisher
/r_shoulder	/torso	RobotStatePublisher
/r_upper_arm	/r_shoulder	RobotStatePublisher
/r_upper_elbow	/r_upper_arm	RobotStatePublisher
/r_lower_elbow	/r_upper_elbow	RobotStatePublisher
/r_lower_arm	/r_lower_elbow	RobotStatePublisher
/r_hip_intercon	/pelvis	RobotStatePublisher
/r_hip	/r_hip_intercon	RobotStatePublisher
/r_thigh	/r_hip	RobotStatePublisher
/r_shank	/r_thigh	RobotStatePublisher
/r_ankle	/r_shank	RobotStatePublisher
/r_foot	/r_ankle	RobotStatePublisher
/camera	/map	Magma
/ball	/map	Magma
/cup_1	/map	Magma
/cup_2	/map	Magma
/cup_3	/map	Magma
/cup_4	/map	Magma
/cup_5	/map	Magma
/opponent_1	/map	Magma
/opponent_2	/map	Magma
/opponent_3	/map	Magma
/opponent_4	/map	Magma
/opponent_5	/map	Magma
/teammate_1	/map	Magma
/teammate_2	/map	Magma
/teammate_3	/map	Magma
/teammate_4	/map	Magma

Table 2. The static coordinate system frame descriptions and its publisher.

Child Frame ID	Parent Frame ID	Publisher Node
/pelvis	/base_link	RobotStatePublisher
/camera	/head	RobotStatePublisher

References

1. Schnekenburger, F., Scharffenberg, M., Wülker, M., Hochberg, U., Dorer, K.: Detection and Localization of Features on a Soccer Field with Feedforward Fully Convolutional Neural Networks (FCNN) for the Adult-Size Humanoid Robot Sweaty. Proceedings of the 12th Workshop on Humanoid Soccer Robots, 17th IEEE-RAS International Conference on Humanoid Robots, Birmingham (Nov 2017)
2. Schnekenburger, F., Wülker, M., Hochberg, U.: Sweaty - Fußballspielender Roboter mit neuronaler Ballerkennung. VDI-Konferenz Humanoide Roboter 2017, Aschheim (Dec 2017)