Report: Room Detector

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Contents

1 Introduction

The room detector uses inputs from several sensors to determine what room or environment the device is currently in. It uses a statistical model to associate ambient factors with a user-defined room number. The network must be trained by the user before it may be used. This is done online by placing the device in each room to be detected, entering training mode, associating either a new or existing room number with the training data, and then moving the device through the room. The longer the device is trained, the more accurate its classifications become. Once training is complete, the device may enter detection mode and be moved between any of the trained rooms. If brought to an untrained room, it will make its best guess at classifying the room as one that was trained.

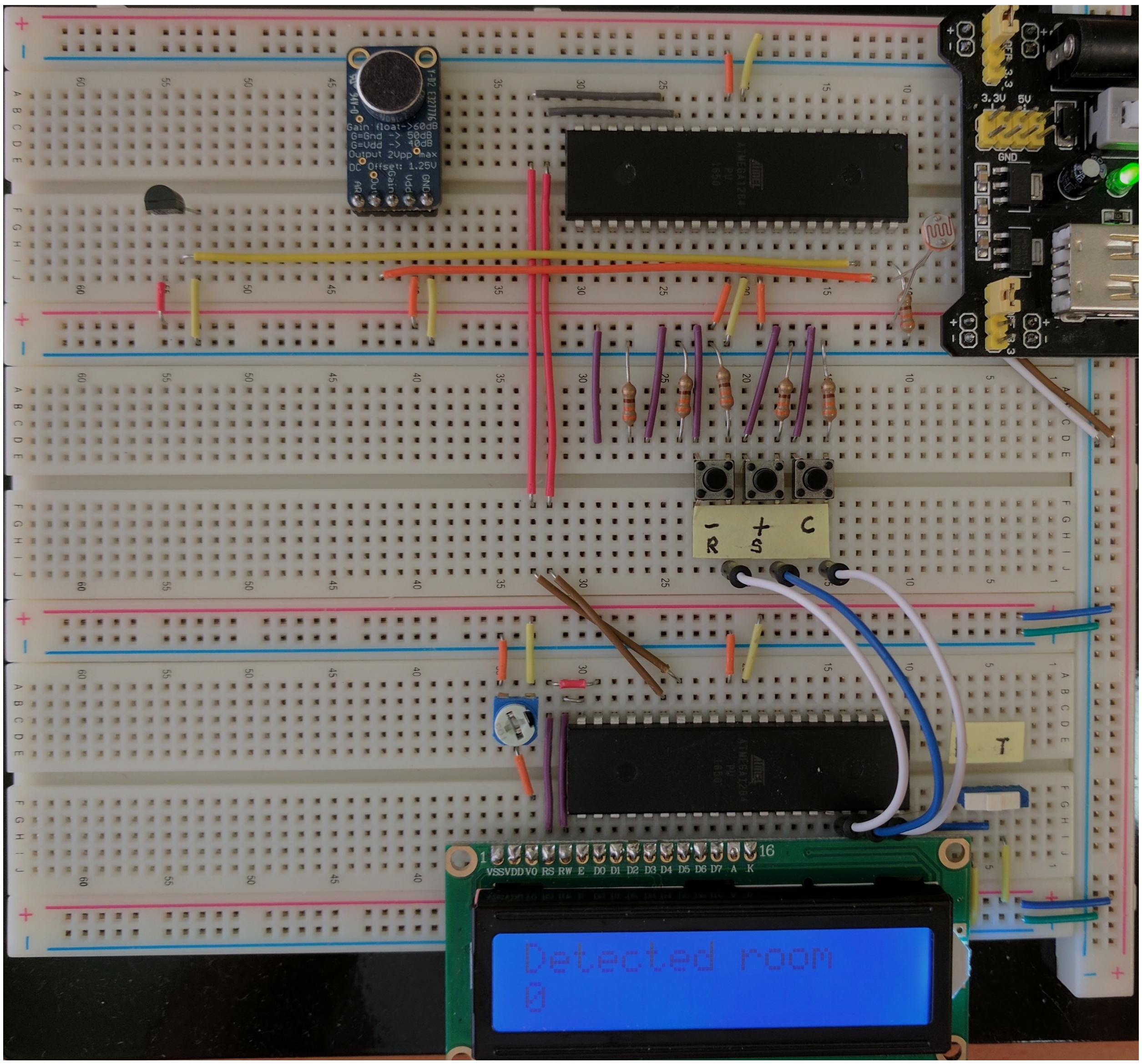


Figure 1: Overview photo of project hardware

2 Hardware

2.1 Parts

The hardware components that were used in this project are listed below. The equipment that was not taught as part of the course material is listed in bold.

Part Number	Component	Quantity
ATmega1284p	Microcontroller	2
	SPDT toggle switch	1
	SPST push-down button	3
	10KΩ trimmer potentiometer	1
	330Ω 10% resistor	4
	CdS photoresistor	1
LCM-S01602DTR/M	Liquid crystal display	1
TMP36	Temperature sensor	1
CMA-4544PF-W	Electret microphone	1
MAX9814	Microphone amplifier	1

Table 1: Listing of parts used in design

2.2 Pinout

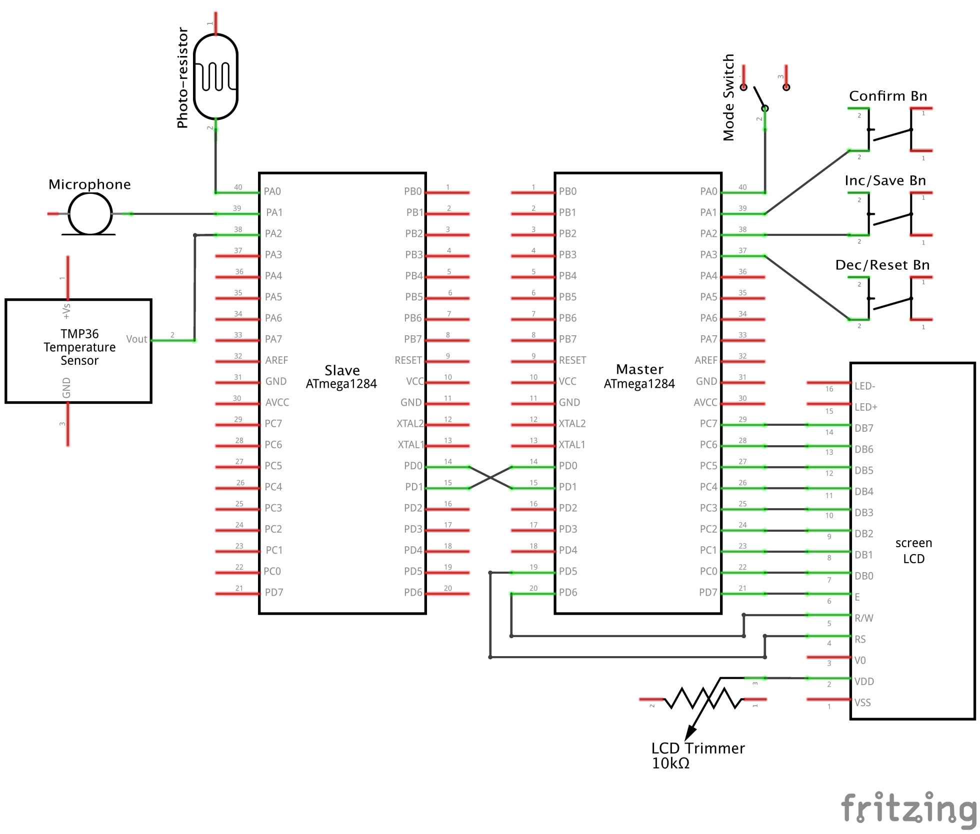


Figure 2: Pinout and schematic for project

3 Software

The software designed for this project was implemented using the PES standard. The overall design as a task diagram is included below.

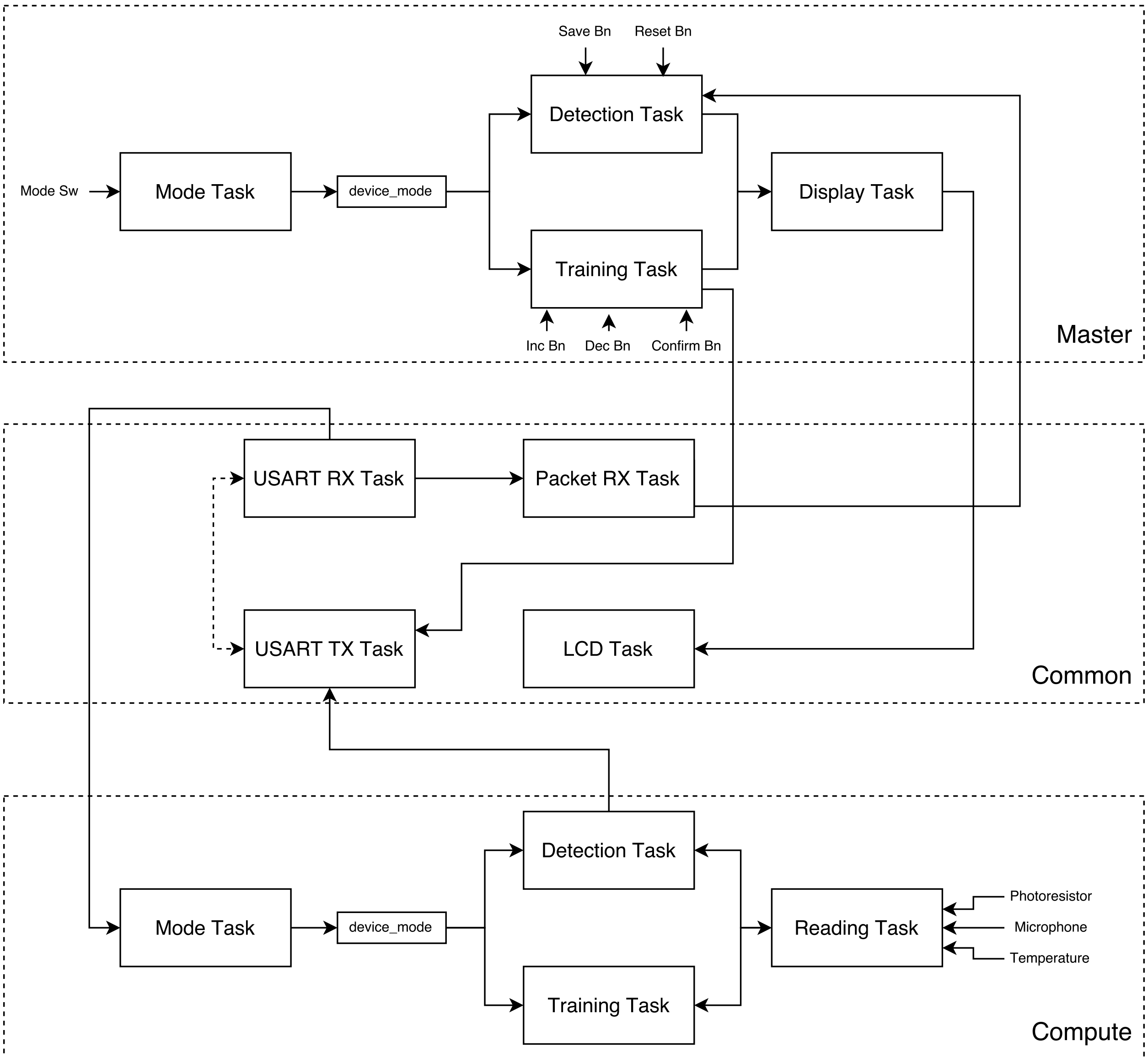


Figure 3: Task diagram for project

The master and compute tasks run on their respective microcontrollers. The common tasks run independently on both microcontrollers, being part of a static library linked to by both microcontroller applications and instantiated in their task schedulers. The inputs and outputs for the common LCD, USART TX, USART RX, and packet RX tasks were excluded from this diagram for brevity but are documented in their task descriptions.

In the following sections, the individual tasks from the above diagram are briefly described in addition to their inputs and outputs. The state machines for these tasks are presented in appendix A.

3.1 Tasks

3.1.1 Master Mode Task

Input `PA0`

Output `device_mode: enum`

Sets `device_mode` to `DETECTION` if `PA0` is low and to `TRAINING` if it's high. This controls which of the detection and training tasks is enabled.

3.1.2 Master Detection Task

Input `device_mode`; `PA2`; `PA3`

Output `detected_room: uint8`; `usart_tx_queue`

Local `tick_count: uint16`

Operates when `device_mode` is `DETECTION`. Receives detection packets from the compute microcontroller. Responds to the save, reset, and erase buttons by sending the appropriate packets to the compute microcontroller to adjust the model.

3.1.3 Master Training Task

Input `device_mode`; `PA1`; `PA2`; `PA3`

Output `training_room: uint8`; `is_training: bool`; `usart_tx_queue`

Local `tick_count: uint16`

Operates when `device_mode` is `TRAINING`. Responds to the increment, decrement, and confirm buttons by adjusting the training room and sending the appropriate packets to the compute microcontroller to begin and end training. Sets `is_training` to true when training.

3.1.4 Master Display Task

Input `detected_room`; `training_room`; `is_training`; `should_display_save`; `should_display_reset`; `should_display_erase`; `is_lcd_ready`

Output `should_lcd_clear`; `should_lcd_write`; `lcd_buffer`; `lcd_position`

Local `last_room: uint8`

Outputs messages to the LCD according to the current state and detected or training room. Controlled by the detection and training tasks.

3.1.5 Compute Mode Task

Input `usart_packet_rx_queue`

Output `device_mode: enum`; `training_room: uint8`

Sets `device_mode` to `DETECTION` when a stop-training packet is received and to `TRAINING` when a start-training packet is received. Sets `training_room` to the room indicated in the start-training packet.

3.1.6 Compute Reading Task

Input `should_poll_readings: bool`; `adc`

Output `reading_vector: accum[]`; `are_readings_ready: bool`

Local `readings: accum[]`; `index: size`; `samples: size`

Samples from the analog inputs in sequence when `should_poll_readings` is true to create the `reading_vector`. Calculates the mean of 16 samples through time to smooth noise. Indicates when the reading vector is populated by setting `are_readings_ready` to true.

3.1.7 Compute Detection Task

Input `device_mode`; `reading_vector`; `are_readings_ready`

Output `detected_room: uint8`; `should_poll_readings`

Classifies the current reading vector using the classification model when `are_readings_ready` is high and `device_mode` is `DETECTION`. Outputs the classification result to `detected_room`.

3.1.8 Compute Training Task

Input `device_mode`; `reading_vector`; `are_readings_ready`; `training_room: uint8`

Output `should_poll_readings`

Integrates the current reading vector into the classification model when `are_readings_ready` is high and `device_mode` is `TRAINING`.

3.1.9 Common LCD Task

Input `should_lcd_clear: bool`; `should_lcd_write: bool`; `lcd_buffer: char[]`; `lcd_position: uint8`

Output `is_lcd_ready: bool`

Local `index: size`

Clears the LCD when `should_lcd_clear` is true. Writes the contents of `lcd_buffer` to the LCD at `lcd_position` when `should_lcd_write` is true. Sets `is_lcd_ready` to true when the current operation is complete.

3.1.10 Common USART TX Task

Input `usart_tx_queue: uint8[]`; `usart_tx_queue_size: size`; `usart_tx_queue_head: size`; `usart_tx_queue_tail: size`

Output `usart_tx_queue`

Transmits bytes over USART from the TX queue.

3.1.11 Common USART RX Task

Input `usart_rx_queue`

Output `usart_rx_queue: uint8[]`; `usart_rx_queue_size: size`; `usart_rx_queue_head: size`; `usart_rx_queue_tail: size`

Receives bytes from USART into the RX queue.

3.1.12 Common Packet RX Task

Input `usart_rx_queue`

Output `usart_packet_rx_queue: usart_packet[]`; `usart_packet_rx_queue_size: size`; `usart_packet_rx_queue_head: size`; `usart_packet_rx_queue_tail: size`

Identifies and receives packets from the USART RX queue into the packet RX queue. When active, non-packet bytes are discarded from the queue–thus only packet communication is possible when scheduled.

4 Complexities

4.1 Complete

- Using EEPROM to persist the classification model state
- Using USART to offload computation to a dedicated microcontroller
- Using ADC multiplexing to collect analog readings from multiple sensors
- Using a temperature sensor and microphone obtained outside of the lab kit
- Using a statistical model to perform input classification using fixed-point arithmetic

4.2 Incomplete

- Using a neural network to perform input classification using fixed-point arithmetic
  This complexity could not be completed due to hardware limitations. Its role in the project was instead filled by the statistical model listed above. The intended design for the neural network was a multi-layer feed-forward network, with one input layer of size 4, one hidden layer of size 10 with a linear activation function, one hidden layer of size 10 with a hyperbolic tangent activation function, one hidden layer of size 16 with a linear activation function, and one output layer of size 16 with a softmax activation function. This topology was chosen as the best for fulfilling the goal of classifying three inputs, with one bias input, into one of 16 outputs. However, this network proved too large for the ATmega to process. When including the amount of memory necessary for storing training state, the network became too large for storage in the ATmega's 16 kilobyte SRAM. Additionally, even using fixed-point arithmetic in place of traditional floating point, the times for classification became slower than was considered acceptable and the times for training made it obvious that training would only be possible offline using a faster device, which was deemed to be beyond the scope of this project. As a result of these limitations, the neural network was replaced with a simpler statistical model at the cost of accuracy and robustness when faced with input noise.

5 Links

Demonstration Video https://youtu.be/Kw6NZRzlpkQ

GitHub Repository https://github.com/nokurn/roomdetect

6 Known Issues

- The classification algorithm does not cope well with noise and may confuse environments with a large degree of noise as being equivalent regardless of the specifics of that noise.
- The temperature sensor is not measured with sufficient precision for its readings to adequately influence the results of the classification.

- The microphone primarily distinguishes between noisy and quiet environments with no consideration of the qualities of the sound such as timbre and pitch.
- The classifier most heavily relies on the measurements from the photo-resistor, despite unbiased treatment of all readings in the input vector. This is likely due to the aforementioned reasons: low analog precision and the need for pre-processing of some readings.

7 Future Work

- The largest improvement might come from replacing the compute microcontroller with a higher-power compute unit, possibly integrating floating-point arithmetic, and using a more robust classification model such as a neural network.
- By using an external analog-digital converter with higher precision, or simply replacing the ATmega with a microcontroller with a higher-precision integrated ADC, sensors with small output ranges would contribute more to the accuracy and confidence of the device's classifications. This would reflect immediately in the ability of the device to distinguish between environments with slightly different temperatures.
- Applying a Fourier transform to the microphone signal and using the individual components as input to the classifier would improve the quality of classifications with regard to environmental sounds. For example, if one room contains several computers with spinning fans and another room has a single ceiling fan, yet the volume level in both rooms is similar, a Fourier analysis of the sound waves would enable the classifier to distinguish between the two by the timbre and pitch of the sound in addition to its loudness.
- Adding additional sensors would increase the size of the classifier's feature vector and its accuracy. Barometric pressure, humidity, altitude, or even GPS would be likely candidates for inclusion in the system.

A Appendix: State Machines

In the following state machines, transitions without conditions should be interpreted to be else-transitions unless the state only has one outgoing transition, in which case the transition is unconditional.

A.1 Master Microcontroller

Figure 4: State machine for master mode task

Input `PA0`

Output `device_mode: enum`

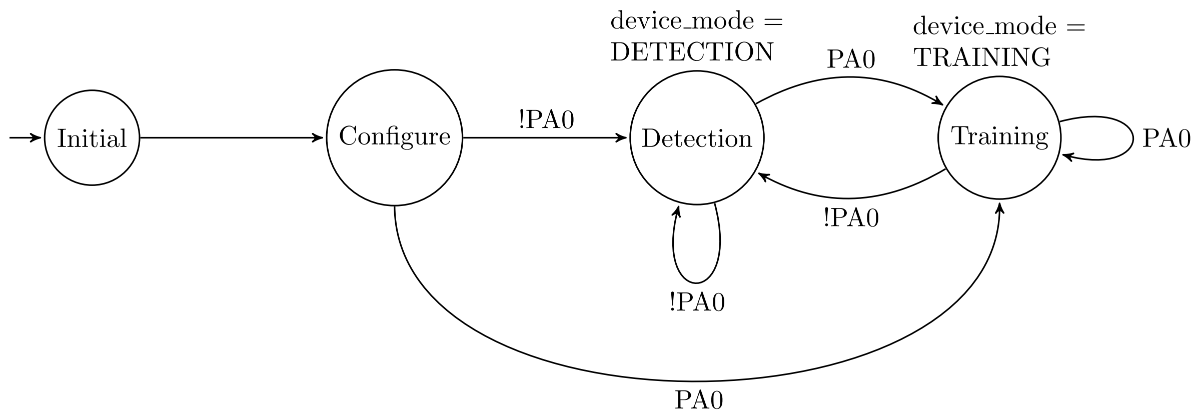
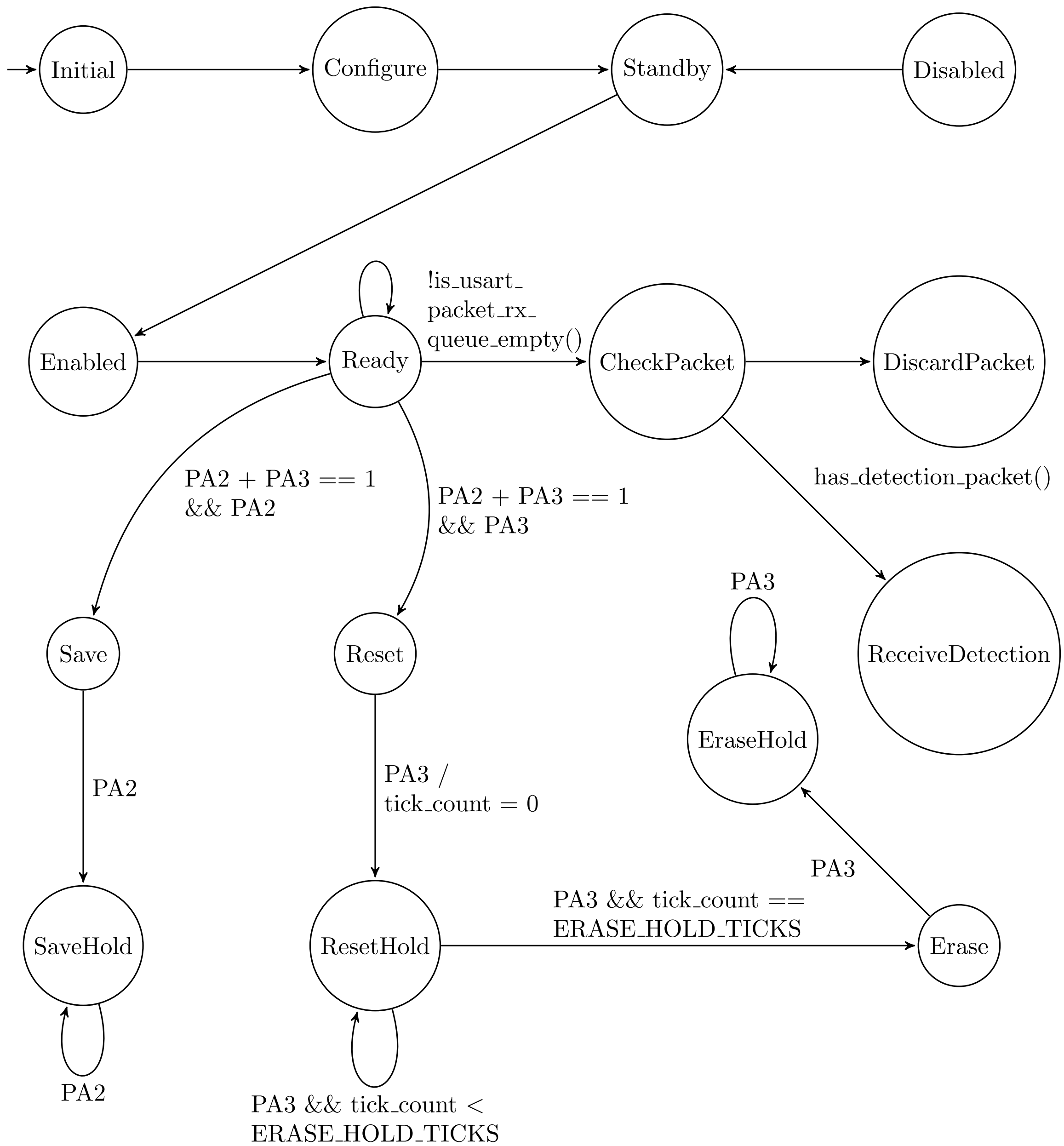


Figure 5: State machine for master detection task

Input `device_mode`; `PA2`; `PA3`

Output `detected_room: uint8`; `usart_tx_queue`

Local `tick_count: uint16`



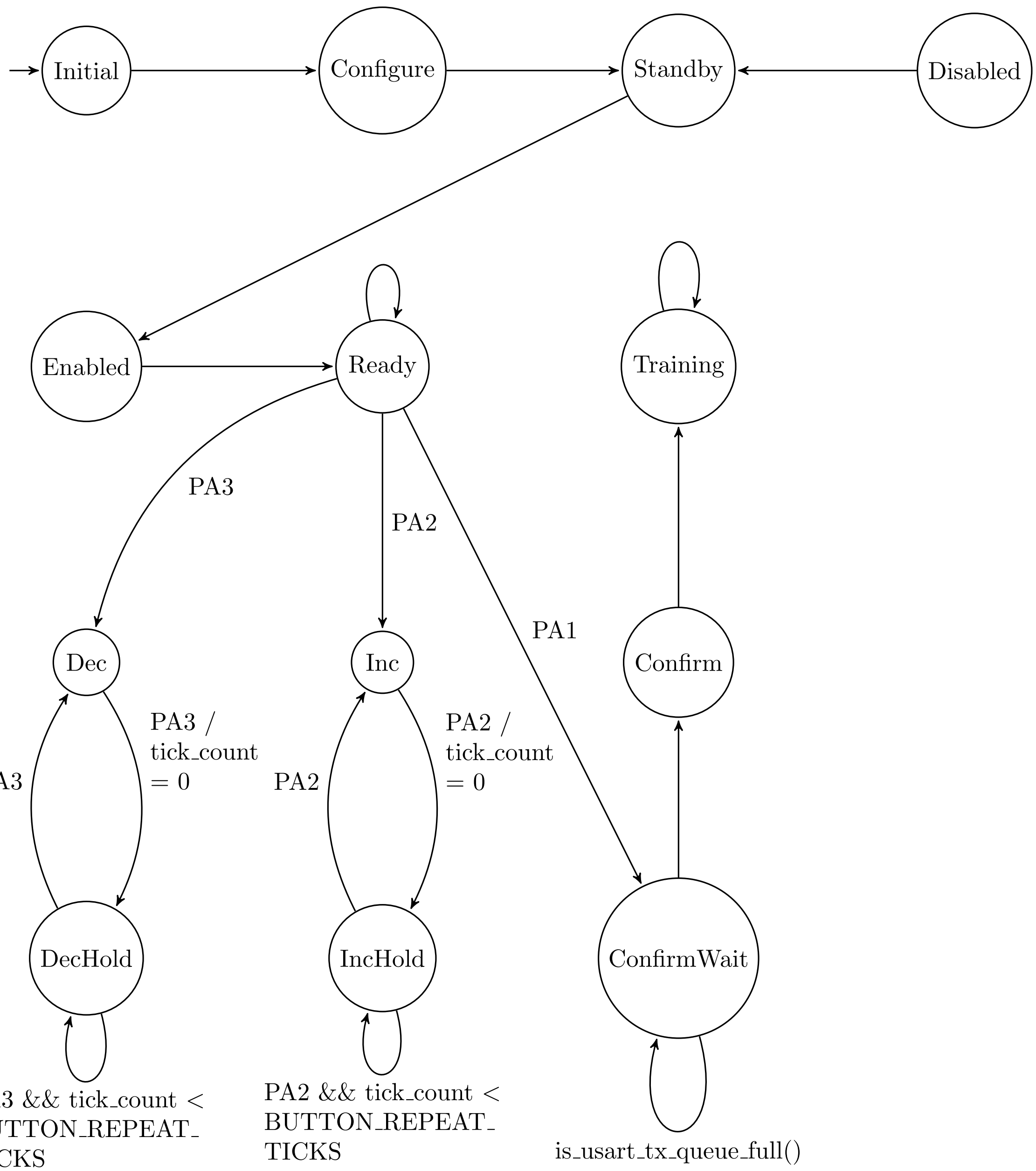
The following transitions have been omitted for clarity: from all states to the Disabled state, under the condition that device_mode != DETECTION; and the else-transitions from the DiscardPacket, ReceiveDetection, Save, Reset, Erase, SaveHold, ResetHold, and EraseHold states to the Ready state.

Figure 6: State machine for master training task

Input `device_mode`; `PA1`; `PA2`; `PA3`

Output `training_room: uint8`; `is_training: bool`; `usart_tx_queue`

Local `tick_count: uint16`



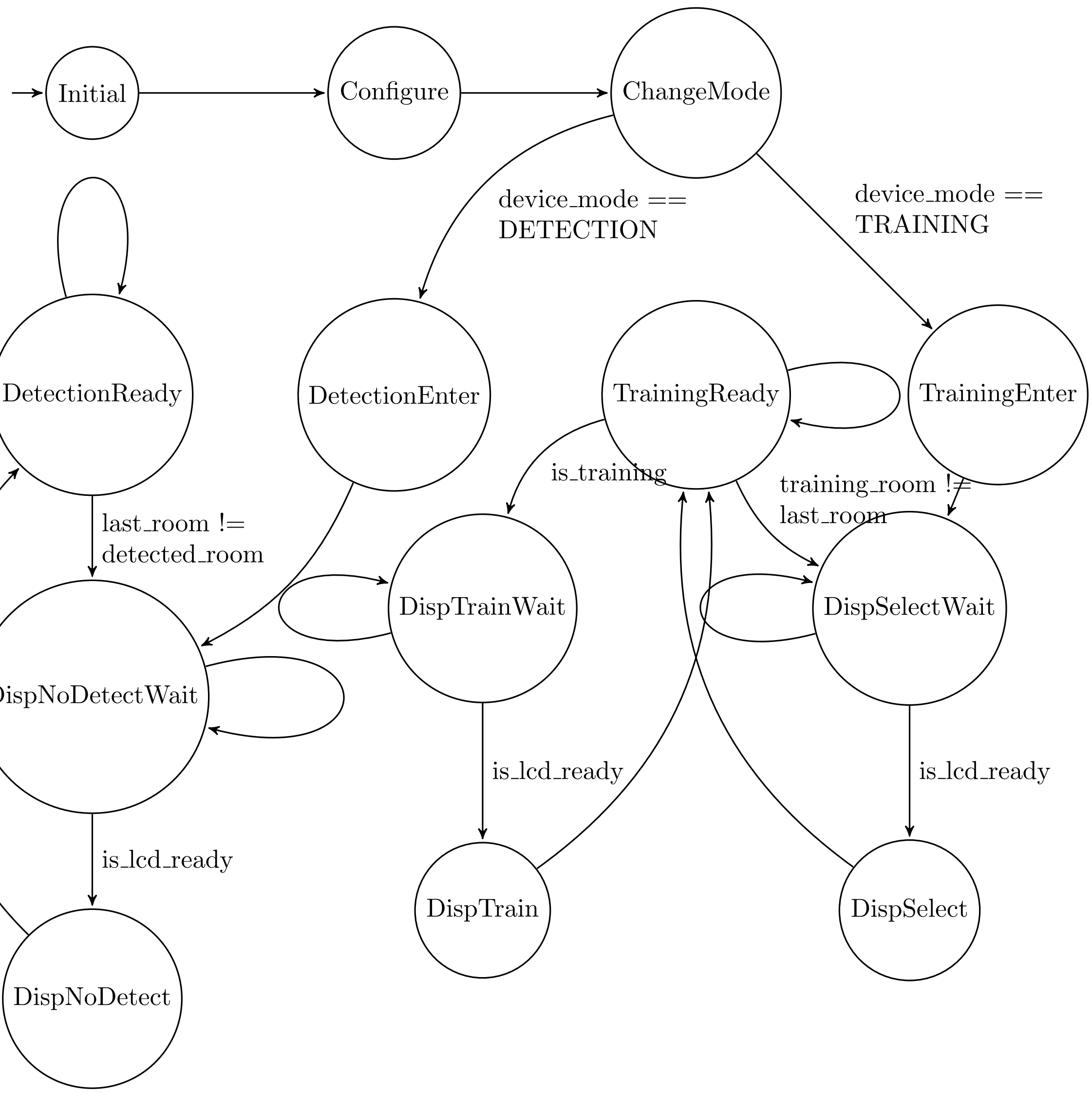
The following transitions have been omitted for clarity: from all states to the Disabled state, under the condition that device_mode != TRAINING; and the else-transitions from the Inc, IncHold, Dec, and DecHold states to the Ready state. The transition conditions from the Ready state to the Dec, Inc, and ConfirmWait states are also conjoined with the condition that PA1 + PA2 + PA3 == 1. The transition conditions from the DecHold and IncHold states to the Dec and Inc states, respectively, are also conjoined with the condition that tick_count == BUTTON_REPEAT_TICKS.

Figure 7: State machine for master display task

Input `detected_room`; `training_room`; `is_training`; `should_display_save`; `should_display_reset`; `should_display_erase`; `is_lcd_ready`

Output `should_lcd_clear`; `should_lcd_write`; `lcd_buffer`; `lcd_position`

Local `last_room: uint8`



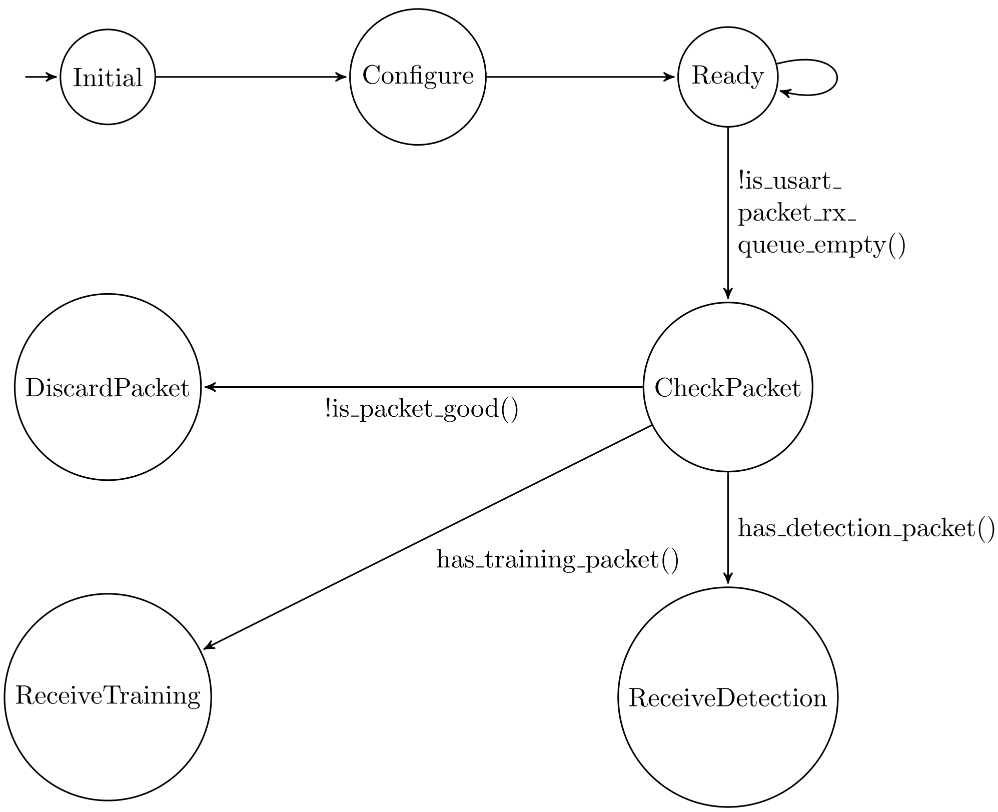
The following transitions have been omitted for clarity: from all states to the ChangeMode state, under the condition that device_mode is different from the expected mode for the given state. The DispNoDetectWait and DispNoDetect states are duplicated, including transitions, for the following similar states: Detect, Save, Reset, and Erase. These redundant states have been omitted for clarity.

A.2 Compute Microcontroller

Figure 8: State machine for compute mode task

Input `usart_packet_rx_queue`

Output `device_mode: enum`; `training_room: uint8`



The following transitions have been omitted for clarity: from the DiscardPacket, ReceiveDetection, and ReceiveTraining states to the Ready state under any condition.

Figure 9: State machine for compute reading task

Input `should_poll_readings: bool`; `adc`

Output `reading_vector: accum[]`; `are_readings_ready: bool`

Local `readings: accum[]`; `index: size`; `samples: size`

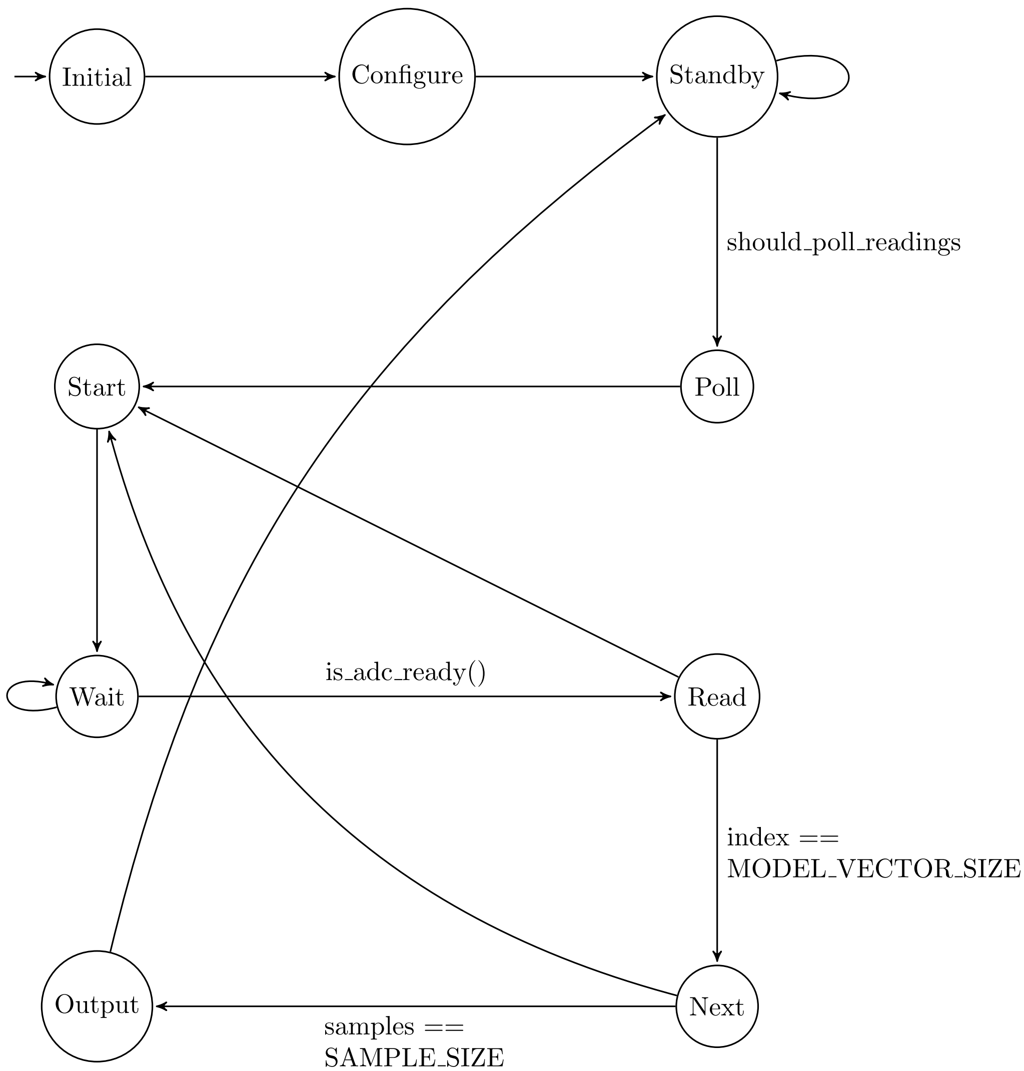
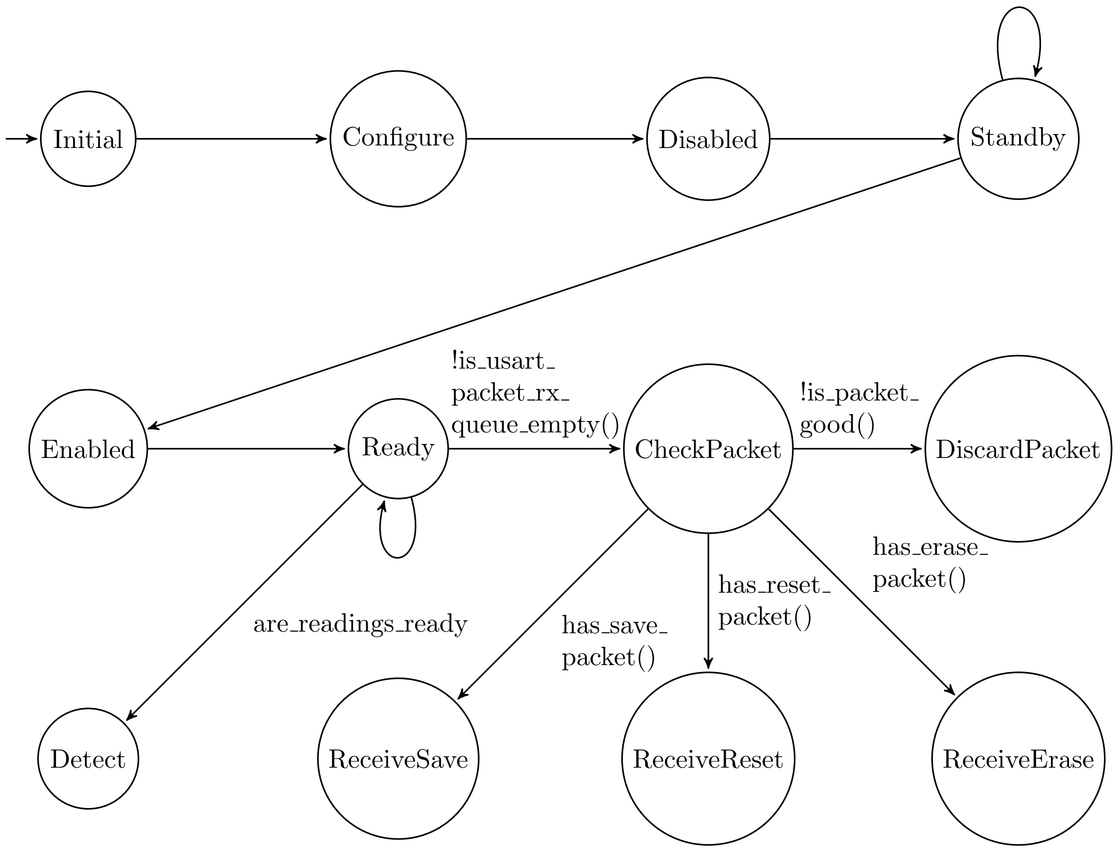


Figure 10: State machine for compute detection task

Input `device_mode`; `reading_vector`; `are_readings_ready`

Output `detected_room: uint8`; `should_poll_readings`



The following transitions have been omitted for clarity: from the Detect, DiscardPacket, ReceiveSave, ReceiveReset, and ReceiveErase states to the Ready state under any condition; the else-transition from the CheckPacket state to the Ready state; and from all states to the Disabled state when device_mode != DETECTION.

Figure 11: State machine for compute training task

Input `device_mode`; `reading_vector`; `are_readings_ready`; `training_room: uint8`

Output `should_poll_readings`

A.3 Common Infrastructure

Figure 12: State machine for common LCD task

Input `should_lcd_clear: bool`; `should_lcd_write: bool`; `lcd_buffer: char[]`;
`lcd_position: uint8`

Output `is_lcd_ready: bool`

Local `index: size`

Figure 13: State machine for common USART TX task

Input `usart_tx_queue: uint8[]`; `usart_tx_queue_size: size`; `usart_tx_queue_head: size`;
`usart_tx_queue_tail: size`

Output `usart_tx_queue`

Figure 14: State machine for common USART RX task

Input `usart_rx_queue`

Output `usart_rx_queue: uint8[]`; `usart_rx_queue_size: size`; `usart_rx_queue_head: size`;
`usart_rx_queue_tail: size`

Figure 15: State machine for common USART packet RX task

Input `usart_rx_queue`

Output `usart_packet_rx_queue: usart_packet[]`; `usart_packet_rx_queue_size: size`;
`usart_packet_rx_queue_head: size`; `usart_packet_rx_queue_tail: size`