Activity Monitoring and Prediction for Humans and NAO Humanoid Robots using Wearable Sensors

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Introduction

Challenges

- Activities (jogging, running) may cause a fall.
- Damage to the human body or to the structural components of the robot.
- Immediate identification.
- Inexpensive wearable sensors.

Motivation

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- Humans and biped humanoid robots have almost identical motions.
- Susceptible to similar accidents.
- Same set of learning algorithms are suitable for both groups.
- Off-the-shelf hardware components to develop our sensing tools.
- Generalized approach for learning and predicting activities of both groups.
- Detection of falls for both humans and robots within a unified framework;

Our Approach and Contributions

Devices

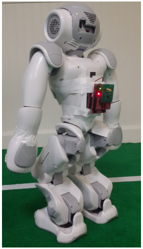
- Configuration:
  1. Tiva C Series TM4C123G microcontroller board.
  2. Sensor Hub BoosterPack for sensing 9-axis motion.
  3. CC2533 BoosterPack for wireless networking.
- Software tools:
  1. Setup the WSN,
  2. Collect data using WSN network,
  3. To learn from sample examples, and
  4. To monitor and predict events.

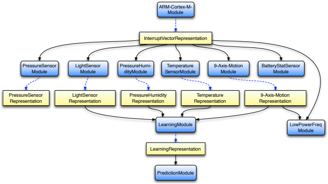
Our Approach and Contributions

Framework

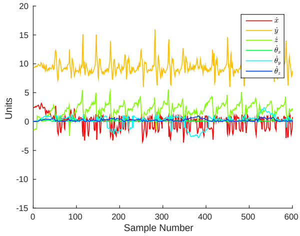
- Generic functionalities to develop applications or rational agents on embedded devices.
- Tools to develop modules and representations that execute on the microcontrollers.
- "μEnergia": `http://muenergia.saminda.org`

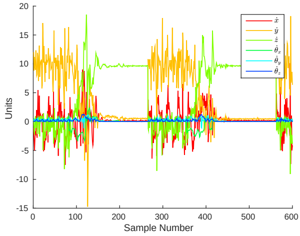
Framework




ARM-Cortex-M-Module
InterruptVectorRepresentation
PressureSensor Module
LightSensor Module
PressureHumi-dityModule
Temperature SensorModule
9-Axis-Motion Module
BatteryStatSensor Module
PressureSensor Representation
LightSensor Representation
PressureHumidity Representation
Temperature Representation
9-Axis-Motion Representation
LearningModule
LowPowerFreq Module
LearningRepresentation
PredictionModule

Activity Annotation





Evaluation Results

Feature Extraction

- $50Hz$ sampling rate.
- In order to identify activities:
  1. Window size of $400ms$ (20 samples); and
  2. Allowed 10 samples ($200ms$) to overlap between windows.
- The selection of the window size is based on the observation that transition from routine activities to a fall event takes between $180 - 250ms$.
- Thus, a window size of $400ms$ will include both fall event and non-fall event data for classification

Evaluation Results

Experiments with a Human

We have conducted twelve motions in total on the human subject.

	Logistic regression				SVM classification			
Activity	**TP**	**TN**	**FP**	**FN**	**TP**	**TN**	**FP**	**FN**
Walking forward	91%	90%	10%	9%	96%	93%	7%	4%
Walking backward	82%	86%	14%	18%	81%	84%	16%	19%
Walking left	86%	86%	14%	14%	89%	90%	10%	11%
Walking right	86%	86%	14%	14%	89%	90%	10%	11%
Falling forward	94%	93%	7%	6%	96%	93%	7%	4%
Falling Backward	84%	88%	12%	16%	84%	87%	13%	16%
Falling left	92%	91%	9%	8%	93%	93%	7%	7%
Falling Right	92%	91%	9%	8%	92%	93%	7%	8%
Marching	91%	90%	10%	9%	95%	93%	7%	5%
Rotate counter-clockwise	91%	89%	11%	9%	93%	91%	9%	7%
Rotate clockwise	92%	89%	11%	8%	94%	91%	9%	6%
Stand to seat	96%	92%	8%	4%	96%	92%	8%	4%

Table: Logistic regression and SVM classification for human activities.

Evaluation Results

Kalman Filtering

- Threshold-based decision making; filtered the roll, pitch, and yaw values using a Kalman filter.
- If filtered roll values are within $[90 \pm 15^\circ]$ and the filtered pitch values are within $[0 \pm 15]^\circ$, then with 100% accuracy, the NAO robot will be in a normal state. Otherwise the robot is in a fallen state.
- If the filtered roll value is less that 60° , the robot is falling forward. If the filtered roll values is more than 100°, then it is falling backward.
- If the filtered pitch value is less than -50°, the robot is falling to the left side, while if the filtered pitch values is more than 50°,then it is falling to the right side.
- With these thresholds for a separate test cases, the thresholding method has detected fallen state with 100% accuracy.

Evaluation Results

Experiments with a NAO Robot

We have conducted eleven motions in total on the robot subject.

	Logistic regression				SVM classification			
Activity	**TP**	**TN**	**FP**	**FN**	**TP**	**TN**	**FP**	**FN**
Walking forward	91%	90%	10%	9%	93%	91%	9%	7 %
Walking backward	90%	90%	10%	10%	93%	91%	9%	7%
Walking left	92%	90%	10%	8%	94%	90%	10%	6%
Walking right	89%	90%	10%	11%	90%	91%	9%	10%
Falling forward	94%	93%	7%	6%	98%	93%	7%	2%
Falling Backward	94%	93%	7%	6%	98%	93%	7%	2%
Falling left	95%	93%	7%	5%	99%	94%	6%	1%
Falling Right	94%	93%	7%	6%	98%	93%	7%	2%
Marching	91%	89%	11%	9%	90%	91%	11%	10%
Rotate counter-clockwise	97%	92%	8%	3%	97%	93%	7%	3%
Rotate clockwise	98%	92%	8%	2%	96%	93%	7%	4%

Table: Logistic regression and SVM classification for robot activities.

Conclusion & Future Work

Conclusion & Future Work

- Learn and predict different activities for humans and robots
- A generic ramework software tools for embedded devices.
- We were able to detect of falls and other activities with high accuracy.
- our future work will be to use multiple sensing devices to create a sensor network.
- Detect complex activities with higher sampling rates.

Thank You