

# 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

- 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:

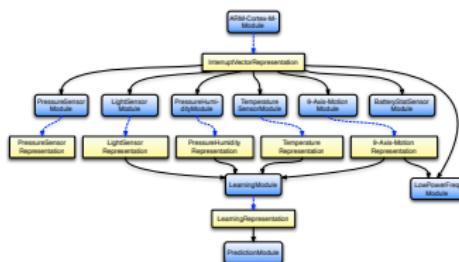
- ① Setup the WSN,
- ② Collect data using WSN network,
- ③ To learn from sample examples, and
- ④ To monitor and predict events.

# Our Approach and Contributions

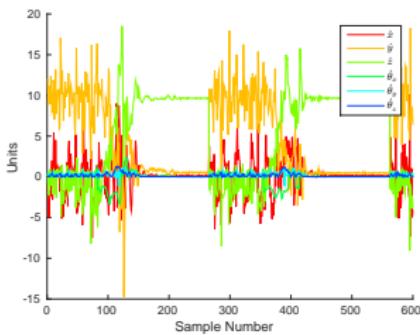
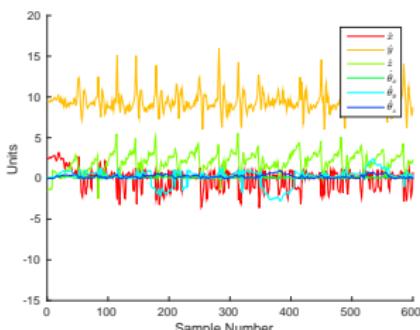
## Framework

- Generic functionalities to develop applications or rational agents on embedded devices.
- Tools to develop modules and representations that execute on the microcontrollers.
- “ $\mu$ Energia”: <http://muenergia.saminda.org>

# Framework



# 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.

Activity	Logistic regression				SVM classification			
	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 than  $60^\circ$ , the robot is falling forward. If the filtered roll values is more than  $100^\circ$ , then it is falling backward.
- If the filtered pitch value is less than  $-50^\circ$ , the robot is falling to the left side, while if the filtered pitch values is more than  $50^\circ$ , 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.

Activity	Logistic regression				SVM classification			
	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

- We proposed methods to learn and predict different activities for humans and robots;
- We also developed a framework software tools to realize these functions on embedded devices.
- We were able to detection of falls and other activities for both humans and robots within a unified framework with 91% – 100% accuracy;
- our future work will be to use multiple sensing devices to create a sensor network to detect complex activities with higher sampling rates.

# Thank You