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

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Outline

1. Introduction
   - Introduction
   - Motivation
2. Our Approach and Contributions
   - Devices
   - Frameworks
3. Experimental Setup
   - Activity Annotation
4. Evaluation Results
   - Feature Extraction
   - Experiments with a Human
   - Experiments with a NAO Robot
5. Conclusion & Future Work
6. *Conclusion & Future Work

Introduction

Challenges in activities in human and biped humanoid robots

- Activity like jogging, running might cause an accident event such as fall. This might cause damage to the human body or to the structural components of the robot.
- Immediate identification of a fall will allow fast responses, and in case of robots it might be able to corrects its motion to prevent accident.
- Though both human and biped humanoid robots share lots of similar features, using same framework it never has been tested to use external embedded devices to identify activities on both.

Motivation

Motivation

- Humans and biped humanoid robots have almost identical movements and are susceptible to similar accidents, we believe that the same set of learning algorithms are suitable for both groups.
- We want to use off-the-shelf hardware components to develop our sensing tools.
- We want to develop a 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

- We have put
  1. Tiva C Series TM4C123G microcontroller board
  2. A Sensor Hub BoosterPack for sensing 9-axis motion
  3. A CC2533 BoosterPack for wireless networking.
- We have developed a set of software tools to create a framework that allow us
  1. To 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

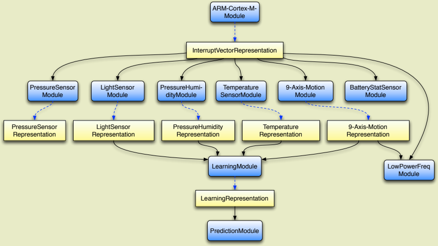
Frameworks

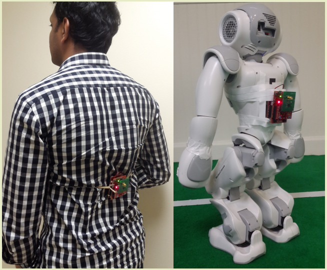
- Our framework provides generic functionalities to develop applications or rational agents on embedded devices.
- The execution paths is ensured using a topologically sorted graph, based on the decision points provided by practitioners.
- The framework includes:
  1. tools to develop modules and representations that execute on the microcontrollers or off-line,
  2. the methods to access functionalities for physical robots, and
  3. a real-time visualization system

  .
- Our development framework, μEnergia (*pronounced as*: "micro–Energia" and *site*: http://muenergia.saminda.org), uses a notion of *modules* and *representations* to perform computations.

Our Approach and Contributions

Frameworks

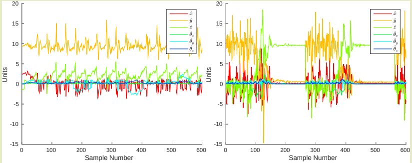




(a) Currently available software modules in our framework and a directed-graph representation of their functional relationship; (b) a wireless sensor device attached to the back of a human subject (c) the same device configuration was used on the back of a NAO humanoid robot.

Experimental Setup

Activity Annotation



Figures (a) shows 3-axis accelerometer and 3-axis gyroscope graph for human motions walking forward Figures (b) shows 3-axis accelerometer and 3-axis gyroscope graph for robot's fallen forward and backward motions.

Evaluation Results

Feature Extraction

- we sampled with $50Hz$ sampling rate.
- In order to identify activities:
  1. we have used a window size of $400ms$ (20 samples); and
  2. we have 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.

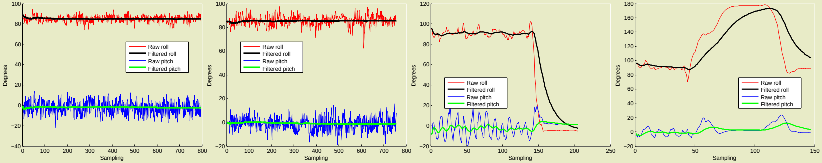
Evaluation Results

Kalman Filtering

- To threshold-based decision making, we have filtered the roll, pitch, and yaw values using a Kalman filter.
- The thresholding method suggests that, if the 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° , we can safely assume that the robot is falling forward. If the filtered roll values is more than 100° we can assume that the robot is falling backward.
- With these thresholds for a separate test cases, the thresholding method has detected fallen state with 100% accuracy.

Evaluation Results

Kalman Filtering



Figures (a–b) show the roll and pitch angles (raw and filtered) for normal behaviors marching in place and walking backward. Figures (c–d) show the raw and filtered roll and pitch angles for fallen forward and backwards states of NAO humanoid robot.

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

- 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.

Thanks for listening

Questions ?