Intelligent Rehabilitation Environment
Room Scale Intelligence & Decision Making
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Arch 879 Fall 2009

General Project Abstract

This project reconceives part of an ongoing project, *comforTABLE*, investigating the use of environmental sensing, inference, machine intelligence and distributed robotics to extend the independence and speed the rehabilitation of those maligned by short- and long-term cognitive and physical impairments. comforTABLE asks, *how can the environment help you to help yourself?* We were charged with rethinking the intent, assumptions, performance and form of the mobile nightstand component of the comforTABLE project.

We began the project with an intensive brainstorming session, similar to an extreme programming event. We spent a continuous twelve hours in a design lab, participating in team and group activities that helped us develop a jointly shared perspective on the nature of the challenge, the opportunities, constraints, intended performance and project trajectory. The session culminated with the identification of a use scenario (critical vs non-critical waking) for the mobile nightstand that we would all address with our designs. (The scenario is presented below.)

We divided into three design teams, each focused on a different performance aspect of the mobile nightstand at a different scale of usability. One team focused on the room scale, addressing sensing, inference and decision making. How does the mobile nightstand understand its context, what are salient cues, how does it differentiate situations and what does it do in each situation? Another group focused on the object scale of the mobile nightstand. What should the mobile nightstand look like, how should it function and what should its interaction with the user be? The third team worked at a component scale. They considered how items should be stored and accessed within the mobile nightstand. All teams collaborated on systems integration.

Room Scale Project Abstract

The room scale project was concerned with evaluating the context of the user in their environment, inferring a specific mode of user activity and performing an assistive reaction by the mobile nightstand.

In the waking scenario, a user's body position and activity level are detected using load cell sensors beneath the four corners of a bed or couch. Using Bayesian analysis, readings from the load cells are processed to determine the user's current posture. One of five postures is inferred: lying, one leg down (as when rising or first retiring), sitting, sitting up (as when waking urgently), or reclining (as when reading or relaxing). Upon detection of one of these postures, a specific response command is issued to the mobile nightstand. An appropriate response by the mobile nightstand is prescribed for various possibilities ranging from routine interaction to critical intervention.

Overhead video facilitates image processing of the bed (couch) and surrounding area to produce an object map of the environment. This map is used by the nightstand to safely and efficiently navigate the space en route to carrying out its assigned task.

Scenario

Joe is in his early 80's and recently installed the mobile nightstand to provide a bit of extra assistance in his home. It provides a little reassurance that his daily activities are augmented by a responsive helper. This makes him feel more secure in his decision to remain in his home, living independently, for a little while longer. The mobile nightstand makes it easier for Joe to keep the daily use items that are most important to him close at hand and organized. In particular, he likes that with the mobile nightstand, his reading glasses, dentures, mobile phone, books, a box of tissues, a glass of water, control of room lighting & the TV, and his medication are never out of reach. Each night when he goes to bed, the mobile nightstand accompanies him into the room, waits for him to lay down and tell it to turn out the lights, and then it positions itself against the wall where it charges.

One night at 2 A.M., the mobile nightstand recognizes that Joe is stirring to wakefulness. In response to Joe's wakefulness, the mobile nightstand positions itself along side the bed within easy reach and signals the lights in the room to come on to a soft illumination. Joe is having difficulty sleeping and decides to read for a while. As he takes his glasses and a book from the mobile nightstand, it signals for the lights to come up fully. It understands that he is okay because it senses where in the room he is located, his bodily position, movement, heart rate, body temperature and respiration. These vitals are normal, Joe's movement is controlled and so the mobile nightstand waits obediently at the bedside until Joe returns his glasses and the book to the nightstand and signals to it to turn out the lights. As he returns to sleep, the device repositions itself along the wall to continue charging until Joe wakes in the morning.

On another occasion, Joe wakes suddenly at 1:00 A.M. The device is aware that his respiration has been increasingly erratic for almost ten minutes, his heart rate started fluctuating moderately three minutes ago and he became very restless before waking. The mobile nightstand has already positioned itself alongside the bed as Joe wakes. It has already brought up the lights. It has positioned itself with the medication drawer open and asks if he would like it to call for assistance. Fortunately, Joe has only suffered some agita from the salmon mousse his neighbor served earlier that day. He takes some medication and leans back, sitting up in bed. The mobile nightstand remains at his bedside, attentive, ready to dial out for help if needed. Within a few minutes, Joe feels better, his vitals are returning to normal and he returns the medication bottle to the nightstand. He says that no call is needed, thanks the mobile nightstand, tells it to turn out the lights and returns to bed.

Materials

Overview
NI LabVIEW was used to acquire and display load cell sensor data. Four 500-lb capacity load cells were deemed sufficient to produce a useful data set. Bayesian analysis was conducted using Matlab. The mobile nightstand was realized using an ActiveMedia Robotics P3-AT mobile robot chassis with an architectural model board form. On board actuation of elevation and rotation was implemented using Parallax servo motors controlled by the Arduino Duemillanove platform. A wireless communication link was used to transmit navigation commands from the Ardiuno to the mobile robot using the ZigBee protocol and using the XBee wireless module. The Arduino is connected to a laptop (on which a learning algorithm runs). It receives data from the load cells. When the learning algorithm detects that there is a change in the state of the person, notifies the Arduino controller. The Arduino then sends that information through the Zigbee protocol to the receiver connected to the Arduino onboard the mobile nightstand. The receiver then takes action based on the signal sent by the laptop.

Inference & Decision Making
LabVIEW was used to capture and display load cell sensor information as shown in the front panel figure below. The LabVIEW Data Acquisition Unit was also configured to transmit the user context (posture) to an Arduino for generation of the wireless command to the nightstand robot. Due to the expansive graphical nature of LabVIEW code, inclusion here is prohibitive.
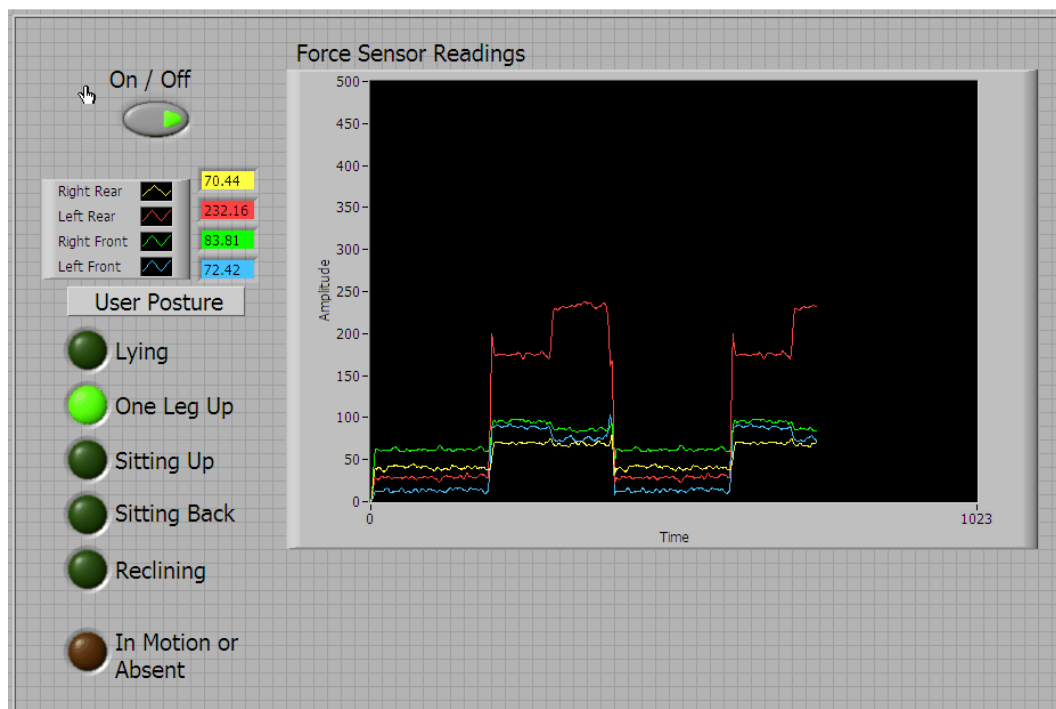
Data Acquisition
The data in this case was acquired from four load cells. Each of the four load cells were placed under the legs of a couch. The data was acquired using two test subjects. Each of the test subjects sat on the couch in five positions. The five positions were:

1. Lying down on the couch
2. One leg up on the couch
3. Reclining on the couch
4. sitting down on the couch
5. sitting up on the couch

The data was recorded in sets of 10 seconds each. Each of the two subjects sat on the couch in the positions mentioned above and the output of the load cells was recorded using LABVIEW. We recorded five sets of data in each of the positions.

Data Analysis
In this section we tried to find out if the data that was acquired in the previous step can be classified into distinct groups. Since a labelled data set is already present it was decided to used supervised techniques to classify the data. Half of the data acquired was used as a training set and the other half was used as testing set. For classifying the data Bayes' rule is used for classification. The Bayes' rule states that:

$$P(X|Z)=(P(Z|X)P(X))/P(Z)$$

P(X|Z) is termed as the posterior. This is the term that we are trying to estimate. P(Z|X) is the likelihood. This term is based on the current observationsof the system. In this case this would be the readings obtained from the loadcells. P(X) is the data prior.

In this case it is assumed that each of the positions is equally likely. As a result of that the prior probability becomes equal to 0.2.

$$P(X)= 0.2 \ (2)$$

In this case we assume that all the classes can be approximated by Gaussian distributions. From the results it can be seen that this is not an unreasonable assumption.So the second term can be calculated as:

$$P(Z|X) = \frac{1}{\sqrt{2\pi|\Sigma|^2}}e^{-(Z-\mu)\Sigma^{-1}(Z-\mu)^T}$$

Z is the vector consisting of the readings obtained from the load cell. μ is the mean of each class obtained from the training data. Σ is the covariance matrix obtained from the training data.

Using the above formulas the probability of the sample belonging to each classis calculated. The data sample is assignedto the classthat has the highest probability.

Class	Training Data	Testing Data
1	0.9954	0.9832
2	0.9979	0.9846
3	0.9969	0
4	0.9992	0.9966
5	0.9963	0.9911

From the results it is seen that the both the training and testing data can be classified with considerable accuracy. In case of reclining the classifier fails because the readings for the test data are radically different training data. The test data for this case falls in classes for one leg up and sitting up instead of reclining.

Code

Arduino Code

```
/*
Aging in Place
Room Level Design
Akshay Apte,Paul Yanik,Joe Manganelli,Linnea Smolentzov
*/

#include <NewSoftSerial.h>
#include <Wire.h>
#include "nunchuck_funcs.h"

NewSoftSerial mySerial =  NewSoftSerial(2, 3);
int loop_cnt=0;

// Variable declaration
int value=7;
int val1,val2;
int lying = 5;
int sitting = 6;

byte condition;  //variable that is used for communication
int count =0;

void setup() {
  //Setup all the pins needed
  pinMode(lying,INPUT );
  pinMode(sitting,INPUT);
  pinMode(13,OUTPUT);
  digitalWrite(lying,LOW);
  digitalWrite(sitting,LOW);

   Serial.begin(57600);

 //Xbee
   mySerial.begin(57600);
}

void loop()                // run over and over again
{
 //if(value==7 || value == 3 || value==4)
  {
   val1=digitalRead(lying);
   val2=digitalRead(sitting);

  if(value==4 || value==7)
  {
  if(val1==HIGH)
  {
    condition=1;
    mySerial.print(condition);  //Send the condition that the person is awake
    delay(5);
    value=0;
    digitalWrite(13,HIGH);
```

```
      }
    }
    if(value==3 || value == 7)
    {
    if(val2==HIGH)
    {
      condition=2;
      mySerial.print(condition);  //send the condition that the person is sleeping

      delay(5);
      value=0;
      digitalWrite(13,LOW);
    }
    }
    }

  //Read the serial port for acknowledgment from the object
  if(mySerial.available())
  {
      value=mySerial.read();
    Serial.println(value);
  }
    //delay(1);
}
```

Matlab Code
```
clc;
clear;

% read the data sets for training
f1=fopen('lying_raghu.txt','r');
f2=fopen('oneleg_raghu.txt','r');
f3=fopen('reclining_raghu.txt','r');
f4=fopen('sitting_raghu.txt','r');
f5=fopen('sittingup_raghu.txt','r');

%read the testing set
f6=fopen('sittingup_raghu.txt','r');

% get the data in proper form

while ~feof(f1)
    data_ly=fscanf(f1,'%f');
end

while ~feof(f2)
    data_one=fscanf(f2,'%f');
end

while ~feof(f3)
    data_rec=fscanf(f3,'%f');
end

while ~feof(f4)
    data_sitd=fscanf(f4,'%f');
```

```
end

while ~feof(f5)
    data_situ=fscanf(f5,'%f');
end

while ~feof(f6)
    data=fscanf(f6,'%f');
end

[r1 c1]=size(data_ly);
[r2 c2]=size(data_one);
[r3 c3]=size(data_rec);
[r4 c4]=size(data_sitd);
[r5 c5]=size(data_situ);
[r6 c6]=size(data);

data_ly=reshape(data_ly,4,r1/4);
data_one=reshape(data_one,4,r2/4);
data_rec=reshape(data_rec,4,r3/4);
data_sitd=reshape(data_sitd,4,r4/4);
data_situ=reshape(data_situ,4,r5/4);
data=reshape(data,4,r6/4);

%calculate the mean and covariances
mean1 = mean(data_ly')
cov1=cov(data_ly')
det1=det(cov1);
mean2 = mean(data_one')
cov2=cov(data_one')
det2=det(cov2);
mean3 = mean(data_rec')
cov3=cov(data_rec')
det3=det(cov3);
mean4 = mean(data_sitd')
cov4=cov(data_sitd')
det4=det(cov4);
mean5 = mean(data_situ')
cov5=cov(data_situ')
det5=det(cov5);

%calculate the probabilities
for i=1:r6/4
    comp=0;

    temp=1/sqrt((2*3.141)^4*(det1));
    temp1 = 0.5*(data(:,i)'-mean1(1,:))*inv(cov1)*(data(:,i)'-mean1(1,:))';
    p_cond(1,1)=temp*exp(-temp1);

    temp=1/sqrt((2*3.141)^4*(det2));
    temp1 = 0.5*(data(:,i)'-mean2(1,:))*inv(cov2)*(data(:,i)'-mean2(1,:))';
    p_cond(2,1)=temp*exp(-temp1);

    temp=1/sqrt((2*3.141)^4*(det3));
    temp1 = 0.5*(data(:,i)'-mean3(1,:))*inv(cov3)*(data(:,i)'-mean3(1,:))';
    p_cond(3,1)=temp*exp(-temp1);
```

```
 temp=1/sqrt((2*3.141)^4*(det4));
 temp1 = 0.5*(data(:,i)'-mean4(1,:))*inv(cov4)*(data(:,i)'-mean4(1,:))';
 p_cond(4,1)=temp*exp(-temp1);

 temp=1/sqrt((2*3.141)^4*(det1));
 temp1 = 0.5*(data(:,i)'-mean5(1,:))*inv(cov5)*(data(:,i)'-mean5(1,:))';
 p_cond(5,1)=temp*exp(-temp1);

 %assign class label
 for j=1:5
    if (p_cond(j,1)>comp)
         comp=p_cond(j,1);
         class(i,1)=j;
    end
 end
end
```

Lessons Learned

Load cells were extremely sensitive to the configuration of the laboratory couch unit and subject user. Minor shifts in the weight of the furniture and user were capable of causing conditions which did not readily adhere to the expected results of our detection algorithm. A more rigid test fixture and more permanent attachment points for the load cells would have aided in the collection of consistent data sets.

Although the analysis used here to characterize user context was effective for the narrow set of cases considered, future work should also include the capacity for adaptive sensing and for sensing of a more broad class of users. To this end, algorithms which allow for greater uncertainty (such as fuzzy logic based inference) and which would provide an improved response over time (such as neural networks) might be employed.

Using the camera to find a path for the mobile nightstand proved to be a difficult task in real time. Due to the processing limitations of the Arduino platform, the computation for the vision analysis, path planning, learning algorithm & inference had to be done on a laptop and then transmitted to an onboard processor on the mobile nightstand. On the mobile nightstand base, the processing required to receive the data and process it in real time also exceeded the capacity of the Arduino platform and thus a second laptop was required to be mounted to the mobile base. In the future, larger micro-controller devices should be tried for processing these larger computational loads.

Future Work

-Identifying different populations and assessing which may be the best sample population for the development of the prototype unit and intelligence (which populations are vital: e.g., rehabilitation setting patients, older adults living at home, nursing home facilities, etc.)
- Designing sensing, inference and intelligence for additional domestic environmental assets (not just sofa or bed, but floor, doors, etc.)
- Designing the behavior and interactive affordances of the system's intelligent agents – will it/they be capable of alerting emergency assistance when required? Will it/they alert a nearby device that can help? Will it/they automatically call 911 or family member?

The information gathered so far is an important step in moving forward with applying the knowledge to a variety of situations. For now it is most important to consider the different populations to be evaluated. For example, populations that might benefit the most from this may be older adults living at home, in a

nursing home facility, or in hospital settings. It may be valuable to note patterns of movement in patients, as well. Furthermore, it will be important to look into other means of gathering data and other areas of the home environment that might be candidates for sensors, in addition to researching how people use each piece of furniture.

A major aspect to consider is how best to use the sensing, inference and intelligence. For example, will it be stored such that care providers can access it to view how a person is moving about their environment? Will it provide a steady stream of information?

Refinement of learning algorithm, vision planning and systems integration is required.

Waking scenarios considered in this implementation assumed a steady state assessment of user posture. Future work would examine temporal aspects of user motion to allow sensing to distinguish between normal and critical situations. Physiological metrics would also be added to the sensed data stream to allow a greater richness of activity feature identification.