Modeling Human Behavior and State

A ROS package for Human Robot interaction

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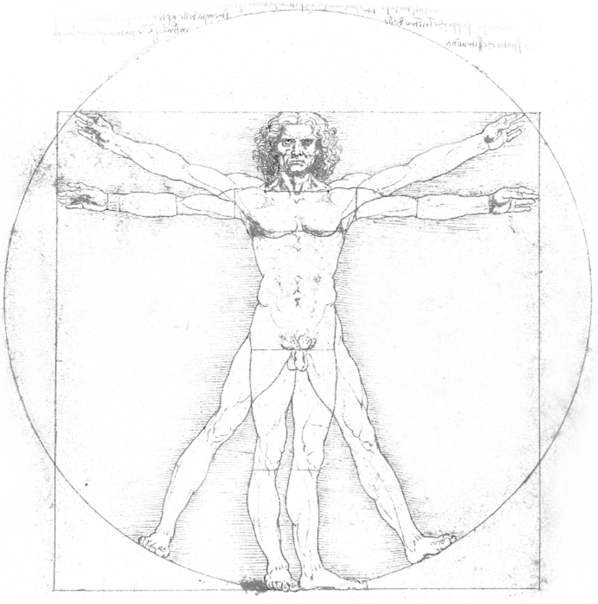

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23rd August 2018

Abstract

Short intro to the project (1/2 pages)

- what is it about (problem)
- what has been done to ready the problem (method, data)
- findings (main findings)
- precautions for the findings
- conclusion
- implications

This work implements an easy to use ROS package for human sensing and prediction for applications in geriatric care. Methods for sensing pose, respiration rate and heart rate are implemented. In addition, models for human activity recognition are implemented and tested. The system also features RoI extraction for some selected body parts.

Preface

TODO: When / Where / COINMAC / Kyushu University

Acknowledgements

I would like to thank Professor Jim Torresen and Vice Dean Ryo Kurazume for the oppurtunity to write this masters thesis at the lab here in Kyushu. TODO: friends, family Humanitude Project [3]

This work is part of a Masters degree in Informatics: Robotics and Intelligent Systems at the University of Oslo. The work was written as a collaboration between the ROBIN lab at the University of Oslo, and the Kurazume Laboratory at Kyushu University as part of the exchange program COINMAC funded by The Norwegian Research Council.

A special thanks goes to my supervisors, Jim Tørresen and Ryo Kurazume, for both providing me with the fantastic oppurtunity to study abroad and for all their support and guidance througout this project.

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Many thanks goes to all my friends and family back in Norway for supporting me despite the vast distance and time difference. At last, I would like to thank my friends Karl Magnus, Soman, Mathias and the rest of the informatics students with whom I started at the university. Thank you for making my time here unforgettable.

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Chapter 1

Background

1.1 Motivation

As life expectancy increases in Norway, so does the population who needs geriatric care either at home, or in a geriatric facility. From [5] we can see that both the number of people in need home nursing is steadily increasing across all amounts of assistance needed. In addtion, the time spent per user has also increased over the years. This means that the time geriatric personnel has, must be spent more efficiently, and with the users that need the most help. We propose a novel robotic system that can monitor an elderly person (from here on called “the user”) living at home and give feedback to healtcare personnel about their health, and how much assistance is needed. The system should also be able to detect and predict abnormal states of the user, and warn the appropriate emergency services.

This work will focus on creating data that can be used to model the current state of the subject, as well as implementing models predicting future states. In this effort we wish to monitor the subject’s medical data such as respiration rate (RR) and heart rate (HR), daily activities and mood, as well as contextual input such as the ambient temperature, weather, nearby objects and current location. Machine learning models focusing on both short and long term prediction is discussed.

1.2 Remote Vital Monitoring

Vital data such as respiration rate (RR) and heart rate (HR) could be useful to detect whether a person is undergoing stress, is relaxed, or help paint a more complete picture of the subject’s current state. The temporal development of the vitals could also be valuable information to first responders in the event of an accident. In this project we will rely on eulerian video magnification [10] to extract this data. The color channel of a camera will be used to detect changes in the color of the skin at

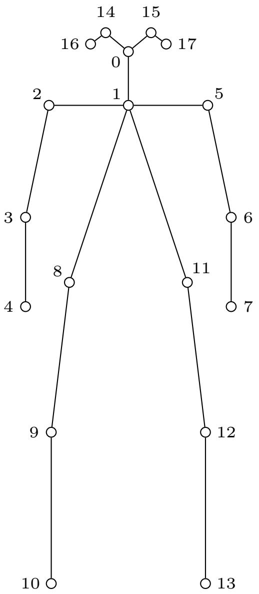

Figure 1.1: Numbering for OpenPose's keypoint markers.

ID	Name
0	Nose
1	Neck
2	Right Shoulder
3	Right Elbow
4	Right Wrist
5	Left Shoulder
6	Left Elbow
7	Left Wrist
8	Right Hip
9	Right Knee
10	Right Ankle
11	Left Hip
12	Left Knee
13	Left Ankle
14	Right Eye
15	Left Eye
16	Right Ear
17	Left Ear

Table 1.1: IDs for OpenPose's keypoint markers.

different keypoints on the face of a person to detect the HR. We also propose to use the depth channel of an RGB-D sensor to detect the rise and fall of a persons chest to estimate the RR.

1.3 Human Pose Estimation

Single view

A lot of work has already been done in detecting human pose, however our system has to work in real life environments where multiple different people can enter the scene. The system also needs to be able to run in real-time if rapid developments are happening. Therefore we will rely on the OpenPose [2] for initial 2D detection of people in the scene. However, to make the system robust to changes in perspective, so we wish to extract the 3D pose of each person using the depth information from an RGB-D sensor. A tracker should also be implemented to ensure object permanence and separate recorded data from multiple people.

1.4 Human Activity Recognition

In this part of the project we will compare Hidden Markov Models to Long Short Term Memory (LSTM) networks to recognize and predict different human activities using datasets such as [8], [4] and [7].

1.4.1 Human habits

We compare Hidden Markov Models to LSTM networks in an effort to detect abnormal patterns in the subject's daily/weekly routines.

1.5 Technologies

1.5.1 Robotic Operating System

The Robotic Operating System (ROS) is a open source framework for building robotic applications used by both academia and in an increasing degree by robots in the industry. ROS provides us with a wide variety of tools and libraries developed by specialized laboratories from around the world. These tools and libraries makes it easier to communicate with different sensors, ready libraries for computer vision and spacial transformations, visualize motion, simulate input and get an overview of the general architecture of the system. In this project we will for example use the iai_kinect2 package [9] as well as the OpenCV library [1].

One of the most useful parts of ROS is that we can easily connect different programs together using ROS messages, topics and pipelines. We can therefore tie together the different parts of this system without much effort, and is why it was chosen as the framework for this project.

1.5.2 Red Green Blue Depth (RGB-D)

An RGDB-D sensor was chosen for this project, as this kind of sensor is already widely used in robotic applications. This makes the package more portable, and can suit many different robot configurations. Using RGB-D data, we also get access to preexisting datasest for training our system. The Microsoft Kinect sensor was used in testing and development.

Stereo vision

Scattered light

Long Short Term Memory

1.5.3

Chapter 2

The Project

2.1 Human Robot Interaction Package for ROS

In this work we implemented a complete system for tracking humans and providing human pose information to ROS.

A multipurpose package for tracking information about humans was made. The package features both detection of 2D joints as well as a method of manually fitting a whole 3D skeleton to the observed points.

2.2 Human Pose Estimation

The robot we're developing needs to be able to robustly detect humans, so information about their state can be gathered and analyzed. To accomplish this task, we propose a system that uses RGB-D data in combination with IR images to estimate the 3D pose of humans. In addition we propose a manual algorithm for estimation of occluded parts that can not be directly observed.

A lot of work has already been done on human pose estimation, however this approach focuses on creating a manual method for constraining the 3D skeleton and estimating the 3D pose of the observed person. We rely on 2D detection of joints for each person by the OpenPose software.

2.2.1 Formulas for constraining

For a fixed point a we want to move a point b so the Euclidean distance between them is equal to L. A few different methods was developed to accomplish this, based on the reliability of the different keypoints.

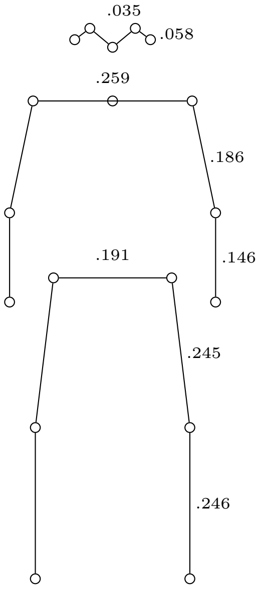

Figure 2.1: Constrained limb connections.

ID	Limb	Model	Pair
0	Left arm	.186	5 – 6
1	Left forearm	.146	6 – 7
2	Right arm	.186	2 – 3
3	Right forearm	.146	3 – 4
4	Hip	.191	8 – 11
5	Left thigh	.245	11 – 12
6	Left leg	.246	12 – 13
7	Right thigh	.245	8 – 9
8	Right leg	.246	9 – 10

Table 2.1: Constrain rules for correct anthropometry. (Note that the anthropometry for the head and shoulders are not yet implemented.)

Keypoint projection

If both $\vec{a}$ and $\vec{b}$ are well-observed points and the initial distance between the point $\vec{a}$ and the line from the camera center through $\vec{b}$ are less than L, we use the following formula to calculate the new position of $\vec{b}$. We get the length, x of the vector to the new position of $\vec{b}$ by using equation 2.1. The constrained point is then simply defined as $x|\vec{b}|$.

$$x = \max\left(\frac{2(\vec{a}\cdot\vec{b}) \pm \sqrt{4(\vec{a}\cdot\vec{b})^2 - 4||\vec{b}||^2(||\vec{a}||^2 - L^2)}}{2(||\vec{a}||^2 - L^2)}\right) \tag{2.1}$$

However, if the minimum distance between $\vec{b}$ and the line is more than L, we define the point as the point L away from point $\vec{a}$ on the line through the coordinates of $\vec{a}$ perpendicular to the line along $\vec{b}$. The point is then defined by equation 2.2.

$$\vec{p} = \vec{a} + L\left|\vec{a} - \frac{\vec{a}\cdot\vec{b}}{\vec{b}\cdot\vec{b}}\cdot\vec{b}\right| \tag{2.2}$$

Keypoint interpolation

This method could be used both to create one additional keypoint, or to determine the location of an obstructed keypoint. We assume we again have two well observed keypoints a and c. We wish to find the location of keypoint b. To interpolate, we imagine two spheres around point a and c with radiuses r_a, r_c. The interpolated point must be on the intersecting circle between the two spheres. The distance from point a to the plane of that circle is defined as $x = \frac{d^2 - r_c^2 + r_a^2}{2d}$ where d is the Euclidean distance $||a - c||$. The radius of the circle is defined as $h = \frac{1}{d}\sqrt{(-d + r_c - r_a)(-d - r_c - r_a)(-d + r_c + r_a)(d + r_c + r_a)}$. The keypoint b is then defined as the keypoint furthest away from the camera on this circle. In later versions this could be constrained by the angle between the previous limb and this one.

2.2.2 Skeleton fitting

We wish to fit a constrained skeleton to the observed points in 3D space. Our skeleton is defined as three separate graphs with constrained edges. The keypoints defining the nodes of the graphs (joints) are detected by the OpenPose network, and sorted based on the confidence of detection. For each graph a subset of n keypoints are picked as seeds, and constrained graphs are generated:
Scale (and thus limb length) is calculated based on the confidence of the keypoints using the weighted sum in equation 2.3 where L is the set of Euclidean lengths in each graph and S is the scores of those lengths. S is calculated by the Gaussian function of the confidence of the scores c_a and c_b with $\sigma = 0.33$ as described in equation 2.4.

$$S = \frac{\sum_{i=0}^{N} L(i) \cdot s(i)}{\sum_{i=0}^{N} s(i)} \tag{2.3}$$

$$s = \frac{1}{\sqrt{\sigma\pi}} e^{-\frac{1}{\sigma}(c_a - 1)^2 + (c_b - 1)^2} \tag{2.4}$$

Alternative notation for equation 2.4 because of possible cumbersome notation in e expression.

$$s = \frac{1}{\sqrt{\sigma\pi}} \exp\left(-\frac{1}{\sigma}(c_a - 1)^2 + (c_b - 1)^2\right)$$

We then recursively constrain all points based on a seed point from the sorted keypoints. If no keypoints with confidence over a certain threshold t are detected, the graph is not placed. The constrained graph is moved to the center of the detected keypoint, again weighted by S, and we are finished constraining the graph.

The skeleton is defined as the subset of graphs best matching their respective keypoints where scale is similar.

2.3 Human Activity Recognition

Time series information to infer the human activity being done.

Neural network is fed, and tries to classify the motion and/or direct pose.

Human 3.6m has 17 different scenarios. We only focus on single person scenarios.

2.4 Pulse and breath detection

Obtain ROI from forehead of subject. chest area for breathing.

Amplify temporal changes in color (or distnace for breathing) values with frequencies that correspond with possible human heartbeats/respiration rate.

Assign as attribute to person in current timestep.

2.5 Facial emotion recognition

Trained direct NN on Radboud Faces Database to recognize emotion.

Chapter 3

Experiments

What did we find out. dont overcomplicate the explanation. this could be the longest part of the thesis. about 15-20 pages? If you have more questions, use that as structure for this section. You can divide this into multiple chapters: subsidiary questions to the main theme, hypothesies, themes. One to three chapters are usually OK. the most important first, main findings. small neuances exceptions and discussions. discuss what youve found. this could be a chapter in itself.

3.1 Individual module experiments

Because of the breadth of this work, a multitude of setups was used to test each part of the system. We also compare our results to ground truth, and established methods.

3.1.1 Pose and joint angle detection

In this experiment we wanted to uncover the accuracy of the 3d joint angles produced by the system, and compare them to other methods and the ground truth. The Human3.6m dataset was used to obtain ground truth for joint positions as well as providing the depth maps and RGBD images for the algorithm. A wide variety of poses were tested, although detection on a variety of ranges from the sensor were not possible using this dataset.

3.1.2 Human Activity Recognition

The dataset in [7] was used to provide training and test data. A few selected behaviors were chosen and recognized.

3.1.3 Facial emotion recognition

We used [6] for training and testing our recognition algorithm. The faces were also scaled down to simulate recognition on a variety of distances from the sensor.

3.1.4 Pulse detection

The pulse was obtained from the forehead, and tested in a variety of lighting conditions. Ground truth and timing was obtained using an in-frame heart rate monitor.

3.2 Complete system test

The complete system was tested in lab conditions on limited hardware, see Appendix B.

3.3

3.4 Results

the main finings, as simply put as possible.

3.5 Discussion

Look at the results critically, weaknesses to the method. discuss how the findings can be explained. reasons to why you found what you found. how it compares to earier research. can reference some earlier theory.

A learning based technique akin to [2] where we instead of training the network on annotated 2D joint and limb locations, we train the network on depth maps might yield good results. One can think that the network would be able to learn the rules of anatomy where corresponding limbs should have roughly equal lengths, and the normal human body proportions. This would result in a bottom-up algorithm that won't be slowed down by having multiple people in frame. The guiding runtime factor would mainly be the size of the image being processed.

Chapter 4

Conclusion

About 10% of the length (means 8̃ pages) often the only thing that is read by people who are just looking at the thesis.

- tell in short version what youve found. main findings first. short, simply put. the neuances and details can be fleshed out in the following sections.
- how your findings fit with earlier work and research. (dont repeat too much from the “earlier research” or “theory” chapters.) What fits, and suggestions as to why.
- The way your finings can have significance. Can we see the subject in a new way? should one change something in practice or how one does things because of your research? can the finds benefit society. Youre going to tell the world, and see what youre writing about in a bigger picture. Can other people learn something from this?

Chapter 5

Future Work

What research is missing, what do we want to know more about, what other methods should be tried out.

Preliminary Notes and sources

This chapter is not to be included in the final thesis. It is only here to provide easy access to relevant research papers while writing.

5.1 Human Pose

How to run NiTE2 on linux for comparison with windows software:

5.1.1 papers

Open Pose paper

Multi view RGB-D approach for pose estimation

Space-time representation of people based on 3d skeletal data

Stacked hourglass networks for human pose estimation

Baseline for human 3d pose estimation from 2d images Accompanying video Github repo

Mocap guided data augmentation for 3d pose estimation in the wild

2D human pose estimation

Determination of 3D human body postures from a single view

People detection and tracking using RGBD cameras for mobile robots Paper direct link

Fast Human Detection in RGB-D Images based on color depth joint feature learning +RoI Extraction

3D skeleton-based body pose Recovery

VNect real time 3D human pose estimation with single rgb camera Project page

Skeletal graph based human pose estimation in real-time

Human skeleton tracking from depth data using geodesic distances and optical flow

Multi-modal Surface Registration for Markerless Initial Patient Setup in Radiation Therapy using Microsoft's Kinect Sensor

Accurate 3D pose Estimation from a Single Depth Image
3D Hand Skeleton Model Estimation from a Depth Image
Key Developments in Human Pose Estimation for Kinect
Single-Shot Multi-Person 3D body pose estimation from monocular rgb input
3D human pose estimation = 2D pose Estimation + Matching
LCR-Net: Localization-Classification-Regression for Human Pose
Image-based Synthesis for Deep 3D Human Pose Estimation
The Vitruvian Manifold: Inferring Dense Correspondences for One-Shot Human Pose Estimation
Learning to recognize affective body postures
Keep it SMPL: Automatic Estimation of 3D Human Pose and Shape from a Single Image

Skeleton Fitting

Skeleton Fitting Techniques for optical motion capture
Progressive Human Skeleton Fitting
Learning Inverse Kinematics for Pose-Constraint Bi-Manual Movements
Local and Global Skeleton FItting Techniques for Optical Motion Capture
3D Body Pose Estimation Using an Adaptive Person Model for Articulated ICP Paper

Head tracking

Face direction using depth maps
Detecting Human Heads with their orientation
POSEidon Face From Depth for Driver pose Estimation
Face Tracking in OpenCV
3D Face reconstruction from 2D images using nn

5.1.2 datasets

Human3.6m dataset for pose Berkeley MHAD (Multimodal Human Action Database)

5.2 Vital detection and mood

5.2.1 papers

Heart Rate detection using Microsoft Kinect Full text
Detecting Heart Rate with Kinect v2 Github repo

Non-contact, Wavelet-based Measurement of Vital Signs using Thermal Imaging

Eulerian Video Magnification for Detecting Subtle changes in the World

5.2.2 datasets

Radboud Faces Database (Emotions)

5.3 Human Activity recognition

5.3.1 papers

Human Activity Recognition system using skeleton data from rgbd sensors
Tracking a Subset of Skeleton Joints: An Effective Approach towards Complex Human Activity Recognition
Human Motion Analysis from Depth data
A simple neural network module for relational reasoning

5.3.2 datasets

Human Activity Detection project at Personal Robotics Lab at Cornell University github repo Dataset by this lab Results

5.4 Other

IAI Kinect2
Facebook's Detectron github repo

5.4.1 papers

Distilling a Neural Network to a soft Decision Tree
Generative Adversarial Nets (GANs)
(RGB-D Indoor Plane based 3d modeling using autonomous robot)
Q learning
Real Time range imaging in health care A survey pdf:
Deep Visual-Semantic Alignments for Generating Image Descriptions

5.4.2 datasets

ETHZurich CVL datasets
    List of RGBD datasets
    Databases 4 kinect

Appendices

Appendix A

ROS package code

The MECS monitor package is the final culmination and implementation of this work.

All packages are different stages of development. They are only here for referencec for now. Remember to remove in final text

- MECS monitor package
- RGBD pose
- KinOP Bridge

Appendix B

Hardware

The hardware used in testing this system. A goal here was to use cheap components that can be implemented in a wide variety of robot platforms.

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