Research Overview

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Online subject-independent probabilistic modeling of sEMG signals from different human joints

Direct control of a prosthetic device
Quick adaptation to a new subject without train phase
Easy to collect

General and robust model
Control of prosthesis or exoskeletons with physiological signals
Quick and easy adaptation to new joints
Subject-independent frameworks

Pre-trained model, refined and adapted to the specific subject to shorten the training phase

Cross-subject analysis by comparing the performances of models built on single subjects when fed with data from different users

Optimized decision tree able to generalize across users without an additional training phase
Multi-user interface which can classify different movements using a bilinear model

T. Matsubara and J. Morimoto, “Bilinear modeling of emg signals to extract user-independent features for multiuser myoelectric interface,” Biomedical Engineering, IEEE Transactions on, vol. 60, no. 8

Regression-based

Continuous estimation of finger movements. Regression methods could generalize to novel movements, not included in the training dataset


Shorten the training procedure starting from a similar known model by minimizing the Mean Square Error (MSE) of the features measured with respect to the ones already processed for a single individual

Interaction with robotic devices controlled by physiological human signals (sEMG)

Human intention of movement ➔ Coherent robot action

Control of wearable devices

Alison Gibson, Mark Ison and Panagiotis Artemiadis, "User-independent hand motion classification with electromyography," ASME Dynamic Systems and Control Conference (DSCC), 2013
Goal *Ready-to-use model:* Good performances since first trials of a new user.

Common underlying behavior in the task performed by different subjects.

Extraction of common constraints by looking to different interpretation of the task.
Actions sequence

Training set (offline)

Multiple Subjects ➔ Recording ➔ Processing ➔ Gaussian Mixture Model

Test set (online)

New Subject ➔ Processing ➔ Gaussian Regression ➔ Robot Simulation
Gaussian Mixture Model (GMM)

\[ P(\zeta^h_j) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\zeta^h_j; \mu_k, \Sigma_k) \]

\[ \zeta_j^h = \{\xi_j^h(t), \alpha_j^h(t)\} \in \mathbb{R}^D \]

- EMG values assumed by the channels at the instant \( t \)
- Angles assumed by the joints at the instant \( t \)

Gaussian Mixture Regression (GMR)

\[ P(\alpha^h | \zeta^h) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\alpha^h | \zeta^h; \hat{\alpha}^h, \hat{\Sigma}_s^h) \]

**Continuous angle estimation**

Bayesian information criterion (BIC)

\[ S_{BIC} = -\mathcal{L} + \frac{n_p}{2} \log N \]
EMG signals are non-stationary Analysis in both time and frequency

Mother wavelet (db2)
Synthesis values $\text{MAV} = \frac{1}{N} \sum_{k=1}^{N} |x_k|$
40 subjects - 6 trials

**Wrist flexion**
Joints: wrist

**“Three” movement**
Joints: interphalangeal and metacarpophalangeal joints of Thumb, Index, Middle and Ring

High number of subjects: analyzed the robustness of the framework

Focus on the independence from the subject more than on the complexity of the motion

Leave-one-out approach: 36 models for each movement tested on the 6 repetitions of the testing subject
\( \rho_{\alpha, \hat{\alpha}} = 0.8224 \)

Correlation and Standard Deviation for the wrist flexion movement. Model built on \( n - i \) subjects and tested on the \( i^{th} \). For every subject the correlation is the mean on 6 trials.

\[ \rho_{\alpha, \hat{\alpha}} = \frac{\text{Cov}(\alpha^h, \hat{\alpha}^h)}{\sigma_{\alpha^h} \sigma_{\hat{\alpha}^h}} \]

\( \rho_{\alpha, \hat{\alpha}} = 0.8067 \)

Correlation and Standard Deviation for the ‘three’ movement. Model built on \( n - i \) subjects and tested on the \( i^{th} \). For every subject the correlation is the mean on 6 trials and 8 joints.
The angle retrieved through the probabilistic model is remapped to the robot motion.
Kick dataset

3 subjects - 60 trials

**SINGLE JOINT**
(knee)

Channels: Rectus femoris, Vastus lateralis and Peroneus longus

Study of the model adaptation to a novel person

**Leave-one-out** approach: data divided in blocks of 10 repetitions

Results improve as new data are added to the model

Correlation and Standard Deviation for the kicking movement. The red line represents the results of the model built on two subjects and tested on the third without updating the model. The blue line represents the results updating the model.
The angle retrieved through the probabilistic model is remapped to the robot motion.
Achieved results

Advantages

- Subject-independent
- Online Regression
- Lightweight model
- Quick and easy adaptation to a new subject

Future works

- New and more complex movements
- Different frameworks comparison
- Combining classification and regression

Novelty

First attempt to remove subject dependency while maintaining online robot control
Taxonomy of hand grasping movements

Taxonomy is the practice and science of classification

Subject-independent online classification of many different movements

Collaboration with Manfredo Atzori at HES-SO, Sierre, Switzerland
16 different grasps organized a hierarchical way dividing power and precision tasks. The closest the leaves the most precise the movement

17 movements organized in a matrix. Goal of creating the taxonomy composed by the largest set of different grasping

Composed tasks

15 groups of movements. Structured classif. of manipulative movements

A quantitative taxonomy is still missing
Rigorous taxonomy based on numerical parameters

General results

Not misinterpreted or imprecise

Analysis of movements from different subjects can extract the common underlying behaviour which characterize every kind of grasp
### Considered movements

<table>
<thead>
<tr>
<th></th>
<th>Movement Description</th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Large diameter grasp</td>
<td>6</td>
<td>Ring grasp</td>
<td>11</td>
</tr>
<tr>
<td>2</td>
<td>Small diameter grasp (power grip)</td>
<td>7</td>
<td>Prismatic four finger grasp</td>
<td>12</td>
</tr>
<tr>
<td>3</td>
<td>Fixed hook grasp</td>
<td>8</td>
<td>Stick grasp</td>
<td>13</td>
</tr>
<tr>
<td>4</td>
<td>Index finger extension grasp</td>
<td>9</td>
<td>Writing tripod grasp</td>
<td>14</td>
</tr>
<tr>
<td>5</td>
<td>Medium wrap</td>
<td>10</td>
<td>Power sphere grasp</td>
<td>15</td>
</tr>
</tbody>
</table>

**NinaPro dataset**

**40 healthy subjects**

**20 grasps**

**6 repetitions for every grasp**
Hierarchical structure
Exploits connections between grasps
Highlights dependence relationships

Features
IAV
MAV
RMS
TD
WL

Considered signals
EMG signals
Exploits muscle activation

CyberGlove signals
Physical aspects of movement

100 ms windows
CyberGlove signals

Dendrogram IAV
Dendrogram MAV
Dendrogram RMS
Dendrogram TD
Dendrogram WL

S1
S2
S40

40 subjects
10 dendrograms/subject
5 EMG, 5 CyberGlove

Dendrograms automatic construction with Matlab
Supertree merge

Dendrogram IAV
Dendrogram MAV
Dendrogram RMS
Dendrogram TD
Dendrogram WL

Subject-independent Dendrogram IAV
Subject-independent Dendrogram MAV
Subject-independent Dendrogram RMS
Subject-independent Dendrogram TD
Subject-independent Dendrogram WL
Subject-independent Dendrogram multi-feature for EMG signals
Subject-independent Dendrogram multi-feature for CyberGlove signals
Subject-independent Dendrogram multi-feature for EMG signals

Subject-independent Dendrogram multi-feature for CyberGlove signals

Subject-independent Dendrogram multi-feature for muscular and physiological signals
Supertree EMG and Glove
Taxonomies from EMG signals and CyberGlove gave similar results.

Differences explained by the analyzed physical characteristics.

General supertree overcome the limitations of the individual taxonomies.

Results comparable with Feix’s taxonomy, the most used one.
## Ongoing works

<table>
<thead>
<tr>
<th>Expansion of quantitative taxonomy for amputated subjects and comparison with healthy subjects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression based online Subject-Independent Modeling of sEMG Signals for the Motion of Robot Joints: expansion to more movements</td>
</tr>
<tr>
<td>Subject-Independent GMM-based online classification of 17 hand grasping movements using EMG signals</td>
</tr>
<tr>
<td>Subject-Independent online classification of 17 hand grasping movements using CyberGlove signals</td>
</tr>
<tr>
<td>Subject-Independent online regression of hand grasping movements using accelerometer signals</td>
</tr>
<tr>
<td>Subject-independent taxonomy based classification and development of a mixed regression-classification framework able to work online</td>
</tr>
</tbody>
</table>
EuRoC Project
Car door module assembly

The positions of door and module could vary of few cm in translations and few degrees in rotation.

Automatic assemblation of a car door with his module.

Benchmarking phase
Industry relevant task
Lightweight Robot
3D sensor camera
Stereo camera
6D force-torque sensor
Vacuum gripper
Screwing tool

IPA facility
IAS-Lab facility
Simulation
Benchmarking tasks

1. Pick and insert door module
   1.1. Locate the door module
   1.2. Pick the module and reach a reference position

2. Screw door module
   - Detecting screw
   - Picking screw
   - Inserting three screws

3. Teach and assemble unknown door
LEARN POSITIONS

Learn the relative positions of each screw hole in module and door

LEARN TRAJECTORIES

Learn the gripping and inserting trajectories through human demonstrations

VISUAL INSPECTION

Identify module and door real positions by visual inspection

PICK AND PLACE

Pick and place the module by transposing the learned motion to real position

SCREWING

The model position is already known, we have to identify screw positions
Description of the Project

Different persons move the Robot → Recording the robot sensors → Data pre-processing → iGMM and Regression → Vision, inverse kinematics and models integration → Task execution
Screw detection movement

Bag files extraction → Joint states → tf

Data processing

Removal of periods in which all joint are still
Kept only data related to the movement

Data from the first repetition made by subject 0
The user manually guide the robot through all the screw holes in the door module.

The system learns the relative positions of the holes.
Learn trajectories – Benchmarking phase

Gripping: complex task

Robot Learning by Demonstration paradigm

Robust model of the movement starting from a series of demonstrations

Few demonstrations needed

Human demonstration kept as short as possible

Robot Learning mixed with Inverse Kinematics

LEARN POSITIONS

LEARN TRAJECTORIES

VISUAL INSPECTION

PICK AND PLACE

SCREWING

The user manually guide the robot to place the module

Also unskilled workers can cooperate with the robot by showing it what to do without any risk

The user manually guide the robot to place the module

Also unskilled workers can cooperate with the robot by showing it what to do without any risk
Probabilistic Model – Benchmarking phase

**Gaussian Mixture Model**

\[ P(\zeta_j) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\zeta_j; \mu_k, \Sigma_k) \]

\[ \zeta_j^h = \{t, \alpha(t)\} \in \mathbb{R}^{D=7} \]

Angles assumed by the joints at the instant \( t \)

**Gaussian Mixture Regression**

\[ P(\alpha|t) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\alpha|t; \hat{\alpha}, \hat{\Sigma}_S) \]

Weighted sum of \( K \) Gaussian components

\( K = 10 \)

6 JOINTS
Object example: Benchmarking

Object Inspection & alignment

Black matt surface
Complex shape
Light reflections and spots
Flexible, moving parts
Picking points
Framework workflow
Object Inspection & alignment

IAS-LAB

Intrinsic Calibration

Stereo Calibration

Intrinsic Calibration

Template Acquisition

Keypoints Extraction & Description

Keypoints Matching

Filtering + Outliers removal (RANSAC)

Triangulation

Identity pose:
\[ c^d\xi_o = I_4 \in SE(3) \]

Reference Object Pose

\( N < \min\{N_L, N_R\} \)

\( \tilde{N} < N \) 2D pairs

\( \tilde{N} \) 3D points

Training (offline)

\( c^d\xi_o \in SE(3) \)

\( M \)

\( \tilde{M} < M \)

\( \tilde{M} \) 3D points

\( \tilde{N} \) 3D points

Retrieving 3D coordinates

Pose Estimation

Image Acquisition

Template Matching

Keypoints Extraction & Description

Filtering + Outliers Removal (RANSAC)

Rect

\( R \)

\( L \)

\( N_L \)

\( N_R \)

\( M \)

\( \tilde{M} \)
Hand-Eye Calibration

Known from kinematics

Useless

\[ e_{\xi_c} = f(b_{\xi_e}^{1...N}, c_{\xi_o}^{1...N}) \]
1. Put a circle grid chessboard into the scene – fixed position
2. Generate (randomly) a set of robot poses/waypoints in such a way the camera can see the chessboard
3. Launch the tool and run the robot motion through each saved waypoint
   NB: the tool does not interact with the robot.
4. Acquire from 50 to 300 couples of: camera_to_object & tcp_to_world
5. Stop the acquisition and wait for the computation of the handeye transform: camera_to_tcp

Developed tool available on Bitbucket: iaslab-unipd/test_hand_eye
Camera-Object pose estimation → \( \xi_o = \hat{\xi}_o \ominus \Delta \xi \)

\[
\xi_c (t + 1) = \xi_c (t) \oplus \lambda^c \xi_{cd} (t), \quad \lambda \in (0,1)
\]

Where:
\[
\xi_{cd} = \hat{\xi}_o \ominus o \xi_{cd}
\]
The diagram illustrates the transformation of frames between the camera and the object.

- \( c^\xi_o(t_0) \) represents the frame at the camera at time \( t_0 \).
- \( c^\xi_c(t_0) \) represents the frame at the camera at time \( t_0 \).
- \( c^\xi_o(t_1) \) represents the frame at the camera at time \( t_1 \).
- \( c^\xi_c(t_1) \) represents the frame at the camera at time \( t_1 \).
- \( b^\xi_{tcp}(t_0) \) represents the frame at the TCP at time \( t_0 \).
- \( b^\xi_{tcp}(t_1) \) represents the frame at the TCP at time \( t_1 \).
- \( tcp^\xi_c(t_0) \) represents the camera frame at time \( t_0 \).
- \( tcp^\xi_c(t_1) \) represents the camera frame at time \( t_1 \).

The equations for frame conversion are:

- \( c^\xi_o(t_0) = c^\xi_c(t_0)c^\xi_o(t_1)^{-1} \)
- \( tcp^\xi_c(t_0) = tcp^\xi_c(t_0)c^\xi_o(t_0)t_{tcp}^c_0c^\xi_c(t_1)^{-1} \)
- \( b^\xi_{tcp}(t_1) = b^\xi_{tcp}(t_0)t_{tcp}^c_0c^\xi_{tcp}(t_1) \)
The robot is able to pick the module task using the model of movement built via Learning by Demonstration.

The task is correctly performed with different facilities and configurations.
The robot inserts the module inside the door using the model of the movement built via Learning by Demonstration.
Freestyle stage
Freestyle phase

Kinect
Trajectory extraction - Freestyle phase

Recorded data

Extracted trajectory
Trajectory extraction - Freestyle phase

Extracted trajectory

Goal

<table>
<thead>
<tr>
<th>x</th>
<th>y</th>
<th>x</th>
<th>y</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.06</td>
<td>1 3</td>
<td>-0.287567</td>
<td>-0.933333</td>
</tr>
<tr>
<td>0.06</td>
<td>3 4</td>
<td>-0.884667</td>
<td>-0.3935</td>
</tr>
<tr>
<td>0.06</td>
<td>2 1</td>
<td>0.310567</td>
<td>0.969833</td>
</tr>
<tr>
<td>0.06</td>
<td>2 3</td>
<td>0.041</td>
<td>-0.300167</td>
</tr>
<tr>
<td>0.941967</td>
<td>0.454267</td>
<td>0.261167</td>
<td>-0.9282</td>
</tr>
<tr>
<td>0.0402</td>
<td>1.0125</td>
<td>0.426267</td>
<td></td>
</tr>
</tbody>
</table>

Radius

x, y coordinates

Insertion coordinates

Exit coordinates
First approach: **trajectory segmentation**

- Circular trajectory
- Rectilinear trajectory

**Too complex approach**

- Already implemented Matlab function
- Many errors
x, y coordinates - Freestyle phase

Area division

Count the number of samples for every cell

Selected the cells with the largest number of samples
Machine Learning based Visual Servoing
**GENERIC IBVS CONTROL SCHEME**

- CURRENT IMAGE → FEATURES EXTRACTION → FEATURES TRACKING → CONTROL LAW → CAMERA VELOCITY
- DESIRED IMAGE → FEATURES EXTRACTION

**HIGH RESOLUTION IMAGE PROCESSING** (Line features extraction)

**CONTROL RATE**
GMM-BASED CONTROL SCHEME

LOW RESOLUTION IMAGES ACQUISITION

NO IMAGE PROCESSING

CONTROL RATE
Lightweight formulation

- Weighted sum of K Gaussian Components
- Model Parametrization $\Theta = \{\mu_j, \Sigma_j, \tau_j\}$ for $j = 1 \ldots K$
- $\sum_{j=1}^{K} \tau_j = 1$

MODEL

$$x = \begin{bmatrix} u \\ y \end{bmatrix} \Rightarrow p(u, y; \Theta) = \sum_{j=1}^{K} \tau_j \mathcal{N}(u, y; \mu_j, \Sigma_j)$$

REGRESSION

$$m_y(u; \Theta) = E[y \mid u; \Theta] = \sum_{j=1}^{K} \pi_j(u; \Theta)m_j(u; \Theta)$$
TRAINING: Visual servoing demonstrations

500x400 ppxs Images @ 55 fps → VS CONTROL LAW → CAMERA VELOCITY

100x1 ppxs horizontal patches → TRAINING DATASET

~10000 samples
Testing: Regression

100x1 pxs Images @ 94 fps

GMR

Camera Velocity

100
90
80
70
60
50
40
30
20
10
0
VS @ 1928x1448
VS @ 500x400
ML @ 500x2

26
55

+52.7%
+41.5%

Camera Limit: 94fps

FPS
FEATURES EVOLUTION & ERROR

$\rho$ slightly variable OFFSET $\rightarrow \sim 1$ mm
CAMERA VELOCITIES

**VISUAL SERVOING**

- Oscillating forward velocity
- Stable x velocities
- Slightly variable height corrections

**GMM-BASED**

- GMM intrinsic averaging
- Oscillation propagation
- Stable height velocity
CARTESIAN POSES

Experiments

Results
PROCESSING TIME

VS = 13.6 ms  →  73 fps

GMM = 0.17 ms  →  5882 fps
Thank you for the attention
Any question?