Application of multi-staged dynamic time warping to upper limbs motion analysis

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Abstract: The method described in this paper can be used to compare three-dimensional upper limbs trajectories between two motion capture (MoCap) recordings. It analysis the kinematic chain using dynamic time warping, starting from hands trajectories, then elbows, arms and finally shoulders. Method generates Dynamic Time Warping align function (DTWaf) of hands which is used to detect local maxima which indicates the part of motions where the highest differences between reference and input recordings are present. Those maxima are used later to compare DTWaf of other body joints and to indicate which body joints caused deviation from the reference. The proposed method is evaluated on dataset containing six exercises performed by a healthy person and persons that suffer cuff muscle pain or shoulder injuries. The results obtained by our method supports the diagnosis of injured subjects which reassures us, that our approach works correctly. The method beside the numerical results enables to generate valuable visualizations that can be used to perform three-dimensional evaluation and comparison of motion ranges between subjects. This approach can be applied for example to support rehabilitation process. By using proposed method physician can easily visualize and measure improvement or deterioration of patient motion abilities comparing it to various reference MoCap.

Key–Words: Motion capture, kinematic chain, dynamic time warping, rehabilitation, motion analysis, signal processing.

1 Introduction

This paper is extended version of conference paper [10]. It has been significantly improved by adding detailed description of motion analysis procedure which includes motion aligning and Dynamic Time Warping align function (DTWaf) analysis. This paper has new and detailed evaluation and discussion of the proposed method on test MoCap dataset. Both dataset and source code can be downloaded and results can be easily reproduced. Beside of already mentioned changes all figures present in this paper have been updated and the state of the art discussion has been extended.

Motion capture (MoCap) technology has many important applications, among them is human motion analysis for rehabilitation purposes. There are many papers describing MoCap usage it this task. For example in paper [1] authors propose a method of upper body posture estimation using a kinematic model and steady-state genetic algorithm. Paper [2] introduces a real-time human arm movement tracking system that can be used to aid the rehabilitation of stroke patients. The project [3] focuses on markerless determination of deviations between the selected bones and joints. The implemented application presents instructional animation of the exercises and verifies the correctness of its performance in real time. Work [4] describes a tele-immersion system for telerehabilitation using real-time stereo vision and virtual environments. Stereo reconstruction is used to capture user's 3D avatar in real time and project it into a shared virtual environment, enabling a patient and therapist to interact remotely. Paper [5] presents inertial sensor-based monitoring system for measuring and analyzing upper limb movements is presented. A kinematic model is built to estimate 3D upper limb motion for accurate therapeutic evaluation. Work [6] describes a vision-based approach for analyzing a Parkinson patient's movements during rehabilitation treatments. Authors in [7] propose adaptive exercise models, motion processing algorithms, and delivery techniques designed to achieve exercises that effectively respond to physical limitations and recovery rates of individual patients.

Dynamic Time Warping is popular technique that is often utilized together with motion capture technol-

ogy for human motion classification [11] [12] [13] [15]. It can be used also for example to limb segments acceleration measurement during functional task performance [14], gait and activity analysis [16][17][18] or simply motion alignment [19].
In contrary to majority of already published papers method presented in this paper is capable to analyze the kinematic chain of upper body joints jointly by comparing two motion capture recordings of persons performing the same exercise. It does not utilize motion derivatives like velocity or acceleration but rather analyze the hand trajectory and then, basing on maxima found in aligned motion paths it detects most important differences between template and input recording in hands kinematic chain. The found differences indicate which body joints caused deviation from the reference path.

2 Material and methods

In this section I will describe kinematic model the proposed method is using, the evaluation approach for motion analysis and validation dataset.

2.1 Features selection

The test dataset was gathered using IMU-based Shadow 2.0 MoCap system. It is consisted of 17 inertial measurement units that contain: 3-axis accelerometer, gyroscope, and magnetometer. The tracking frequency was set to 100 Hz with 0.5 degree static accuracy and 2 degrees dynamic accuracy. The hierarchical kinematic model that was used during data acquisition procedure, that is a part of kinematic model of MoCap system, is presented in Figure 1 – left.

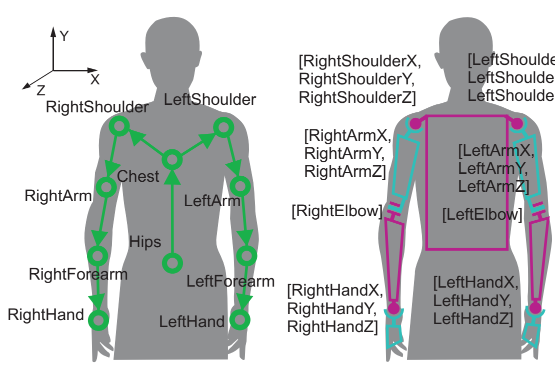

Figure 1: Left – a part of hierarchical kinematic model that is an output of our MoCap. Right – kinematic model that was used in our research for motions evaluation.

For motion analysis the proposed method uses the following kinematic model, similar to one presented in [1] (see also Figure1 – right). At first the coordinate frame relative to shoulder coordinates is defined:

$$\begin{cases} \overline{xt} := \frac{RightShoulder - LeftShoulder}{\|RightShoulder - LeftShoulder\|} \\ \overline{zt} := \frac{\overline{xt} \times [0,1,0]}{\left\|\overline{xt} \times [0,1,0]\right\|} \\ \overline{yt} := \frac{\overline{xt} \times \overline{zt}}{\left\|\overline{xt} \times \overline{zt}\right\|} \end{cases} \tag{1}$$

This frame is used to calculate the rotation angles of upper body parts. Angles are calculated as projection of vector representing the limb onto plane designated by pair of vectors from (1). Shoulder and arm rotation angles are calculated according to following formula:

$$\begin{cases} \overline{v} := LeftShoulder - LeftArm \\ or \\ \overline{v} := RightShoulder - RightArm \\ or \\ \overline{v} := LeftArm - LeftForearm \\ or \\ \overline{v} := RightArm - RightForearm \end{cases} \tag{2}$$

Then the normal vector of the plane is calculated:

$$\overline{n} := \overline{xt} \times \overline{zt} \tag{3}$$

and projection of $\overline{v}$ onto plane with normal $\overline{n}$:

$$\begin{cases} \overline{proj\_y} := \overline{v} - (\overline{n} \cdot (\overline{v} \cdot \overline{n})) \\ angle\_y := \measuredangle(\overline{proj\_y}, \overline{xt}) \end{cases} \tag{4}$$

Rest of the angles are calculated as follow:

$$\begin{cases} \overline{n} := \overline{yt} \times \overline{zt} \\ \overline{proj\_z} := \overline{v} - (\overline{n} \cdot (\overline{v} \cdot \overline{n})) \\ angle\_z := \measuredangle(\overline{proj\_z}, \overline{yt}) \end{cases} \tag{5}$$

and

$$\begin{cases} \overline{n} := \overline{zt} \times \overline{xt} \\ \overline{proj\_x} := \overline{v} - (\overline{n} \cdot (\overline{v} \cdot \overline{n})) \\ angle\_x := \measuredangle(\overline{proj\_x}, \overline{zt}) \end{cases} \tag{6}$$

As the elbow joint rotate in only one plane, elbow angles can be calculated in the following way:

$$\begin{cases} RightElbowAngle := \measuredangle(RightArm - RightShoulder, \\ \quad RightArm - RightForearm) \\ LeftElbowAngle := \measuredangle(LeftArm - LeftShoulder, \\ \quad LeftArm - LeftForearm) \end{cases} \tag{7}$$

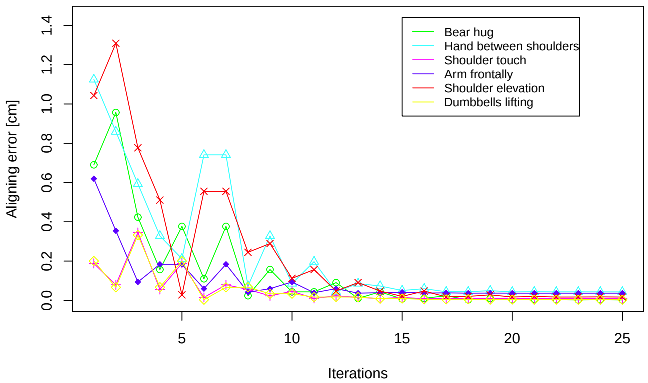

Figure 2: This figure presents aligning error plot which is a result of the DTW aligning procedure.

2.2 Data evaluation

The proposed approach compares the three-dimensional hands trajectories between two experiments participants. The goal is to compare the differences in upper body performance (shoulders, arms and elbows, motion is expressed with angles defined in previous section) between two subjects. Those might be for example a healthy person (a reference recording - Ref) and person with some disabilities (input data - In). We also have to standardize the body proportions between both recordings in order to make them comparable. It can be done for example by using only the body proportions of the reference person. Applying different body proportions in hierarchical kinematic chain is straightforward and does not require further explanation. Also recalculation of hierarchical to direct kinematic model is well defined [8].

Let us assume that the hips (root of kinematic chain) joint coordinates of both input and reference MoCap is constants and equals [0,0,0] during whole recording. That means that all other joints coordinates are described relatively to this joint. In order to start analysis, two motion capture recordings have to be aligned to each other so that vectors designated by shoulder coordinates of reference and input data (8) were parallel.

$$\begin{cases} \overline{V1} := [RefShoulderLeft.X, 0, RedShoulderLeft.Z] \\ \quad -[RefShoulderRight.X, 0, RedShoulderRight.Z] \\ \quad \overline{V2} := [InShoulderLeft.X, 0, InShoulderLeft.Z] \\ \quad\quad -[InShoulderRight.X, 0, InShoulderRight.Z] \end{cases} \tag{8}$$

Where: $RefShoulderLeft.X$, $RefShoulderLeft.Z$ are X and Z coordinates of left shoulder joint in reference recording in direct kinematic model while $InShoulderLeft.X$, $InShoulderLeft.Z$ are X and Z coordinates of left shoulder joint in input recording in direct kinematic model.
We want to find an angle α that minimizes dot product between vector $V1$ rotated around Y axis and $V2$ vector:

$$M_{rotY}(x)) = \begin{bmatrix} cos(x) & 0 & sin(x) \\ 0 & 1 & 0 \\ -sin(x) & 0 & cos(x) \end{bmatrix} \tag{9}$$

$$f_{min}(x) = min(V1 * M_{rotY}(x) \cdot dotv2) \tag{10}$$

Where $*$ is vector by matrix multiplication and $\cdot$ is dot product.
This is one-parameter optimization procedure that is solved using simplex method. In proposed solution simplex starts from initial angle $x_0 = 0$ and performs optimization until obtaining coverage. In the next step the same optimal angle α is applied to rotate all body joints coordinates of input MoCap. Because motion description is described relatively to root joint, this rotation can be easily done just by multiplication of vector with joint coordinates by rotation matrix (9).
All motions are calculated relatively to the chosen left or right shoulder depending which hand we want to evaluate. Let us assume that we want to calculation motion relatively to left shoulder. In order to do so proposed method iterates through all motion samples using Algorithm 1:

Next we need to align reference and input MoCap so that they have common left or right shoulder coordinate (depending which hand we want to evaluate). This is relatively easy operation presented in Algorithm 2.

After applying Algorithm 1 and Algorithm 2 both reference and input MoCap are initially preprocessed and ready to calculate features (1) - (7).

The hand position is an effect of motion of whole kinematic chain that includes shoulder, arm and elbow rotation. Proposed approach aligns three-dimensional trajectories of hands between input and reference signal and calculates the output signal with distances between input and reference MoCap using dynamic time warping (DTW) with Euclidean distance measure. Then so called DTW alignment function (DTWaf) is calculated. DTWaf is generated using following approach:

- DTWaf has length of the input signal.

Algorithm 1: Recalculates motion relatively to left shoulder coordinates vector.

Data: $ShoulderLeft[a]$ - three dimensional vector holding left shoulder coordinates in data sample with index a. $AllJoints$ are are all vectors that have body joints coordinates, instruction $AllJoints[b] \leftarrow AllJoints[b] - diff$ menas that we modify all joints coordintates in our dataset by subtracting them by diff value.

Result: After applaying this algorithm AllJoints are calculated relatively to left shoulder coordinates vector.

for *a in 1:number_of_samples - 1* **do**
  $diff \leftarrow ShoulderLeft[a+1] - ShoulderLeft[a, signal1]$;
  for *b in (a+1):number_of_samples* **do**
    $AllJoints[b] \leftarrow -AllJoints[b] - diff$;

Algorithm 2: Aligns reference and input MoCap so that they have common left shoulder coordinate.

Data: In are coordinates of input MoCap, Ref are coordinates of reference MoCap.

Result: After applaying this algorithm reference and input MoCap have common left shoulder coordinate.

$diff \leftarrow In.ShoulderLeft[1] - Ref.ShoulderLeft[1]$;
for *a in 1:number_of_samples* **do**
  $In.AllJoints[a] \leftarrow In.AllJoints[a] - diff$;

Algorithm 3: Calculates DTW alignment function (DTWaf) of RefSignal and InSignal.

Data: RefSignal and InSignal are multidimensional signals to align, warping_path_length is a length of warping DTW paths WarpingPathRef and WarpingPathIn of Ref and In signals (both warping paths have same length), FUN is a distance function (in this case it is Euclidean distance).

Result: DTW alignment function (DTWaf) of RefSignal and InSignal.

$idprev \leftarrow -1$ **for** *a in 1:warping_path_length* **do**
  $id \leftarrow WarpingPathIn[a]$;
  $vec_1 \leftarrow RefSignal[WarpingPathRef[a]]$;
  $vec_2 \leftarrow InSignal[WarpingPathIn[a]]$;
  if $id \neq idprev$ **then**
    $DTWaf[id] \leftarrow FUN(vec_1, vec_2)$;
  else
    $DTWaf[id] \leftarrow max(DTWaf[idprev], FUN(vec_1, vec_2))$;
  $idprev \leftarrow id$;

- Values of DTWaf samples are calculated using Algorithm 3.

Then we investigate in which samples are the largest differences are in hand positions between participants of evaluation. Those differences can be found as local maxima of $DTWaf$. Knowing the temporal coordinates of samples in which maxima were detected, we can check if similar maxima are present in preceding elements of kinematic chain (elbows, arms and shoulders). If those maxima are also present we can suspect, that largest differences of hand trajectories are caused by differences discovered that way.
In order to detect local maxima we use the following method: signal is smoothed with Gaussian kernel sized $smoothSize = 0.1$ of the input signal. Local maxima are found in smoothed signals using straightforward approach: Extreme is present in data sample with index a when:

$$derivative[a] > 0 \cap derivative[a+1] < 0 \quad (11)$$

Where $derivative$ is first derivative of $DTWaf$. We take into account only those maxima, which have value above certain treshold:

$$\begin{cases} (smoothdata[a] - min(smoothdata)) \geq \\ \qquad ((min(smoothdata) \\ -max(smoothdata) \cdot extremumtreshold) \end{cases} \quad (12)$$

Where $extremumtreshold = 0.66$. After detecting all local maxima in hand $DTWof$ we can perform alignment of all other features (1) - (7). In order to do so following algorithm is performed:
For each feature:

1. DTW aligning between reference and input MoCap is performed using warping path that was calculated for hand;
2. we calculate DTWaf for this feature using Algorithm 3;
3. we detect local maxima in new DTWaf using (11) and (12);
4. we check if those signals also have maxima that are in similar temporal moments like in hand signal. We take into account only those maxima that are in range: $[t - ceiling(length(In) \cdot smoothSize)$, $t + ceiling(length(Ref) \cdot smoothSize)]$ where t is a moment of time where maximum on $DTWaf$ of hand is detected and length is number of samples in a signal. This heuristic is used because displacement in kinematic chain is proportional to the length of the signal and kernel size. Besides detecting maximum we can also indicate parts of the motion preceding the maximum, which caused large values in $DTWaf$. That region of interest (ROI) can be defined as set of sample preceding maxima that has positive value of derivate and begins on the first sample with negative derivate. The role of ROI is to show the fragment of motion that leads to largest displacement between input and reference MoCap.

2.3 Dataset

Six types of exercises have been recorded that can be used to visualize the injuries of upper body. Trajectories of arms motion of those exercises can be seen on three-dimensional renderings in Figure 2. Those exercises were: bear hug, dumbbells liftings, shoulder touch with right hand, rising right arm frontally, touching between shoulders with right hand and shoulder elevation. Same exercises were performed by a healthy subject (reference data) and persons suffering some minor injuries (input data). Participants with disabilities suffered a rotator cuff muscle pain or shoulder injuries. Table 1 presents frames (samples) count of test MoCap dataset were used in this research. As can be seen in Table 1 all reference MoCap was performed faster than input recordings (they have less samples). That was because injured persons struggled more trying to perform actions correctly.
In Figure 2 a reference motion is green while input motion is red. Corresponding samples of MoCap recordings are marked with blue lines. Yellow line indicates frames in which maxima in DTWaf were detected. On the left from person visualization the coordinate frame is presented (1) which is calculated from first frame of reference MoCap. Orange line is an X axis, white one Y axis, and black Z axis.

Table 1: This table presents frames (samples) count of test MoCap dataset that was used in our research.

Action	Reference	Input
Bear hug	151	240
Dumbbells lifting	179	327
Shoulder touch	193	294
Rising arm frontally	160	247
Hand between shoulders	241	327
Shoulder elevation	286	417

3 Results

In order to evaluate the proposed method I have applied it to dataset described in previous section. The implementation of this method has been done in R language and can be downloaded together with a dataset from [9]. Values of aligning procedure error presented in Figure 2 indicate that simplex-based approach introduced in Section 2.2 coverages giving a stable solution. After evaluation, I have made visualizations of obtained results and confront them with disabilities that those people suffered. In Tables 2-7 I present values of DTWaf functions for various exercises. I take into account only those signals in which local maxima satisfy conditions described in Section 2B (are above threshold and within a certain range from maximum detected in DTWaf of hand motion). Figures 4-9 visualize selected DTWaf of those exercises. Among all possible plots I have presented hand DTWaf and one shoulder, arm and elbow angle DTWaf provided that local maximum that satisfies conditions described in Section 2B has been detected.

4 Discussion

Hand trajectories analysis in Figure 2 performed with DTWaf approach prove that maxima detected by proposed algorithm corresponds to parts of motions where there were highest difference in motion range between reference and input MoCap. Three dimensional renderings from Figure 2 gives general concept of difference between analyzed motion pairs however to get precise results plots from Figure 4-9 and values from Table 2-7 have to be analyzed. For example in case of Bear hug motion (see Figure 4), only one maximum with a sufficient value over threshold has been detected. This ROI corresponds to the last part of motion that indicates the inability of an injured person to dynamically move right arm back in XZ plane. As can be seen the basic statistic calculated from DTWaf supplies us with information how much two motions present on MoCap differs from each other. The values are either with cm (hands trajectories) or radians (shoulder, arm and elbow rotation angles). In all cases minimal values (that are often present at initial part of the motion) are close or equals zero but during motion execution those values becomes higher giving relatively high maximal value. This maximal value is good indicator how limited is a motion range of injured person. Generally mean and median value does not differ much between each other and give general numerical concept of averaged distance between motion trajectories on DTWaf plots.

In this experiment detected ROIs correspond to part of motions that indicates the inability of an injured person to dynamically move right arm back in a certain plane which is caused by an injury. Thise results support the diagnosis of injuries described in section 2.3.

5 Conclusion

The research presented in this paper proves that the proposed method is useful for evaluation of upper body motion analysis. The method beside the numerical results enables to generate valuable visualizations that can be used to perform three-dimensional evaluation and comparison of motion ranges between subjects. This approach can be applied for example to support rehabilitation process. By using proposed method physician can easily visualize and measure improvement or deterioration of patient motion abilities comparing it to various reference MoCap. It might be either MoCap of other, healthy person or of the same subject before or during various stages of injury.

Table 2: This table presents minimal, maximal, median and mean value of DTWaf of Bear hug exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.

Feature	Min	Median	Mean	Max
Hand [cm]	0.46	3.98	6.86	31.21
ShoulderZ [rad]	0.00	0.11	0.11	0.29
ArmX [rad]	0.00	0.06	0.10	0.49
ArmY [rad]	0.00	0.06	0.09	0.49
Elbow [rad]	0.00	0.09	0.10	0.24

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References:

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[2] H. Zhou, H. Hu and N. D. Harris, Wearable inertial sensors for arm motion tracking in home-based rehabilitation, Intelligent Autonomous Systems, 9: 930–937, 2006.

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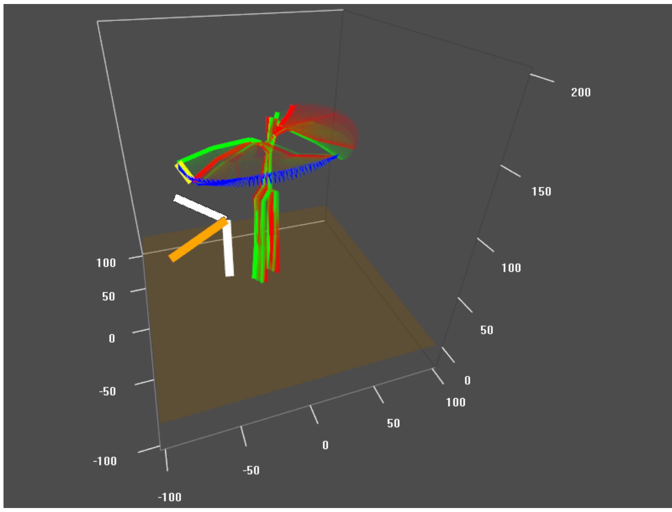
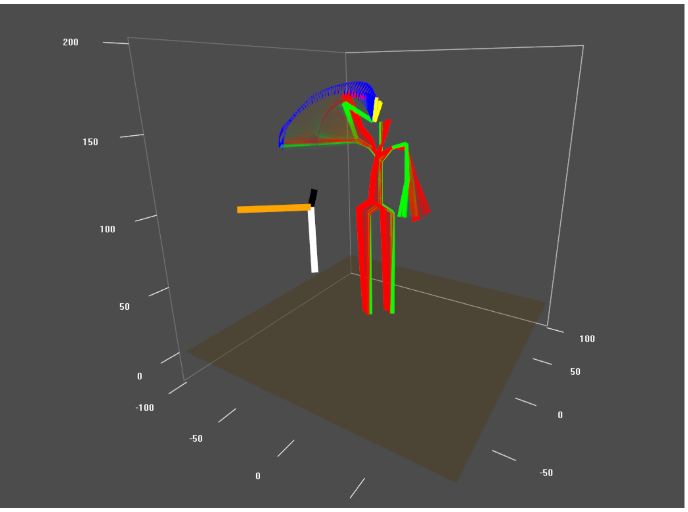
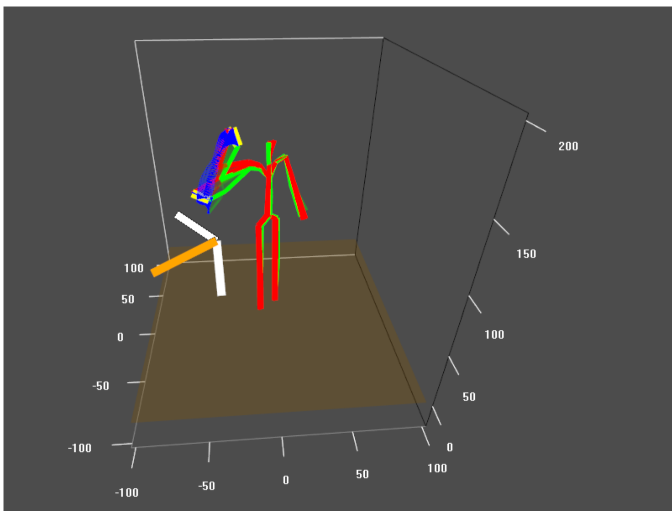


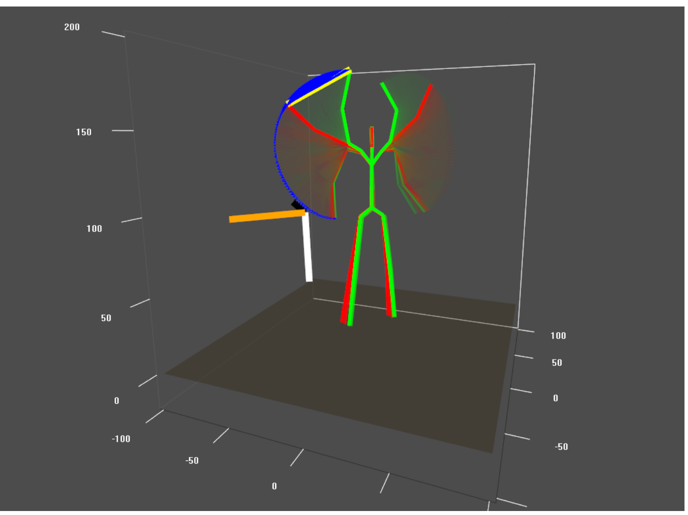
(a) Bear hug



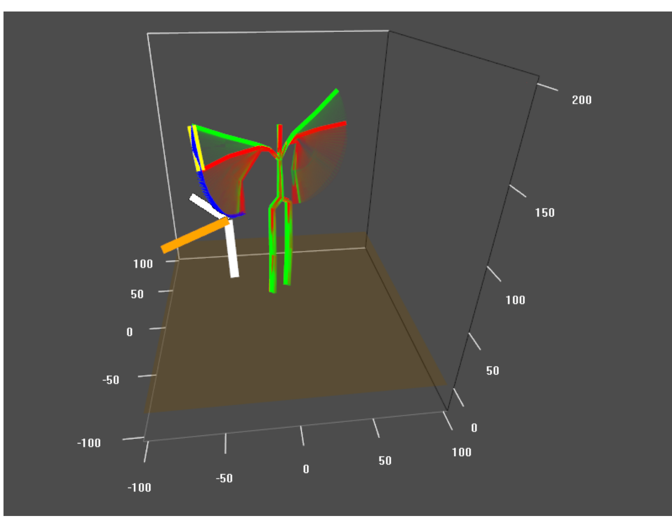
(b) Touch between shoulders on the back



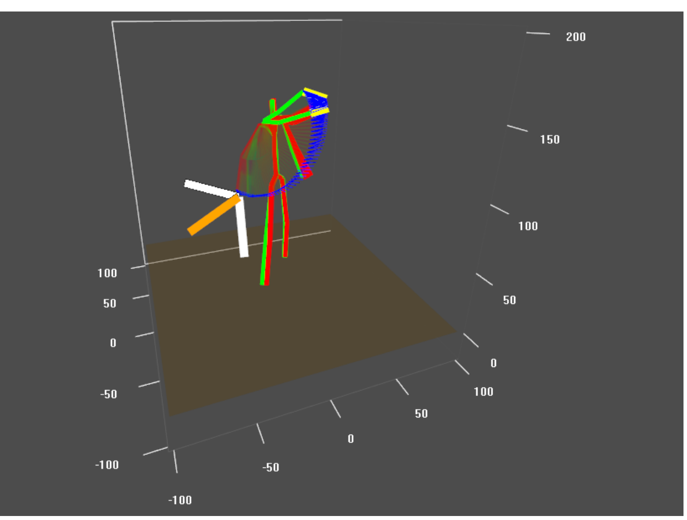
(c) Touch shoulder



(d) Shoulder elevation

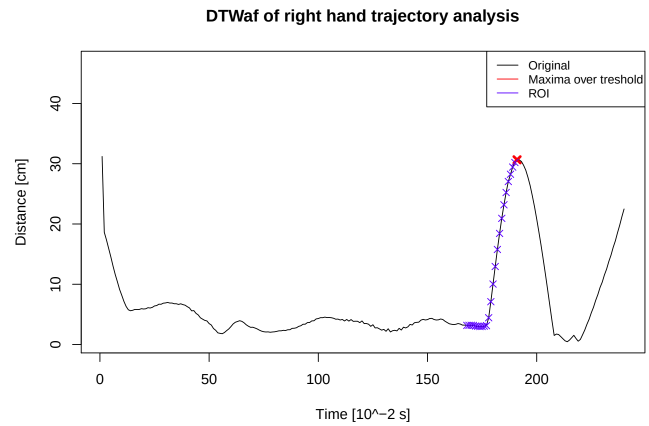


(e) Dumbbells lifting

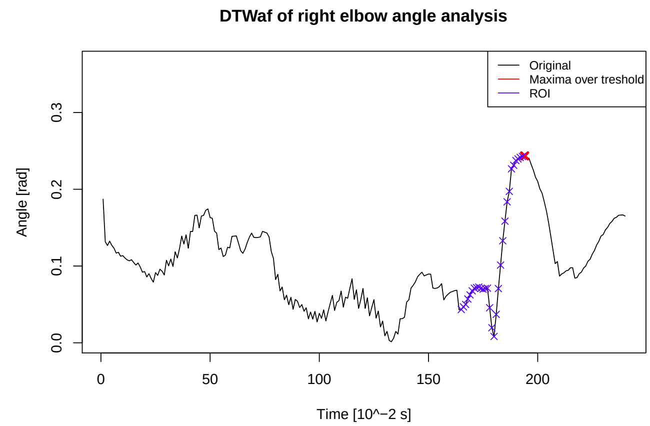


(f) Rising arm frontally

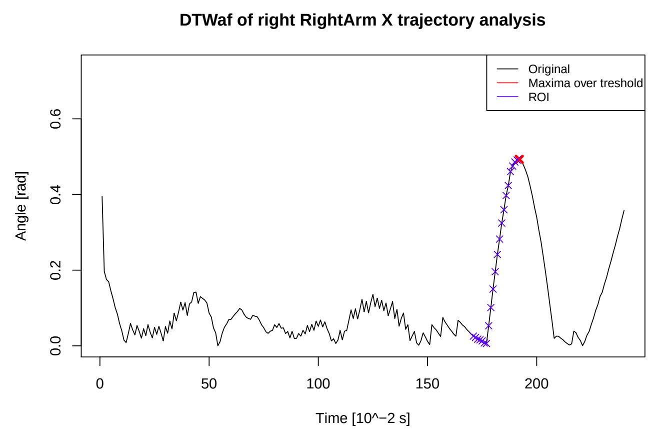
Figure 3: This figure presents three-dimensional renderings of a reference MoCap aligned with input MoCap.



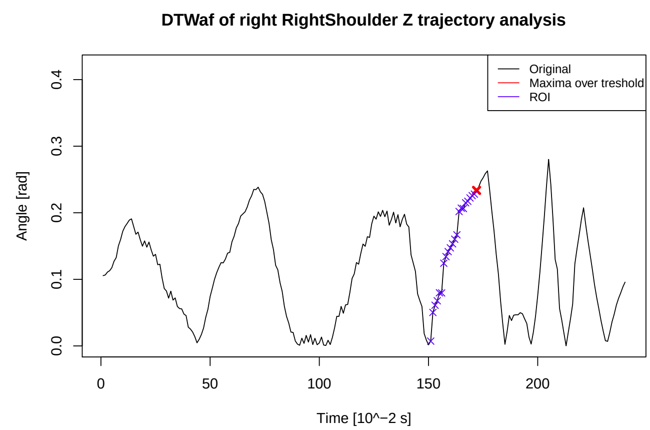
(a) $DTWaf$ of right hand



(b) $DTWaf$ of right elbow angle

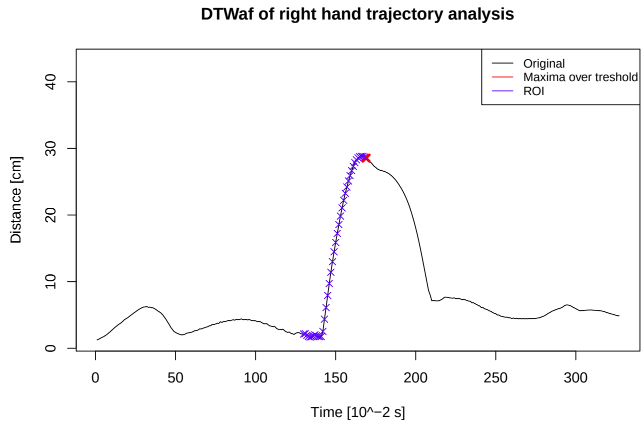


(c) $DTWaf$ of right arm rotation around X axis

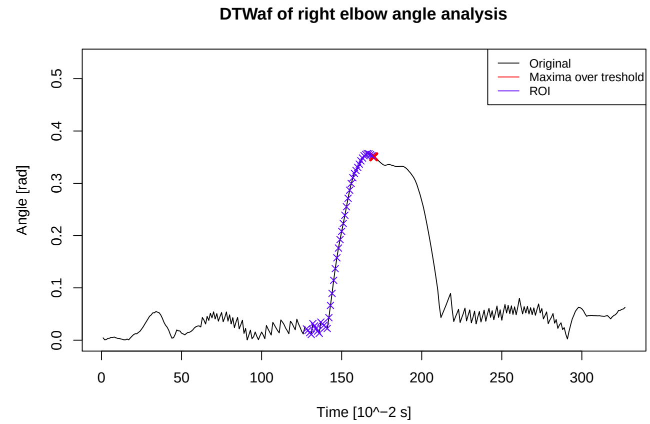


(d) $DTWaf$ of right shoulder rotation around Z axis

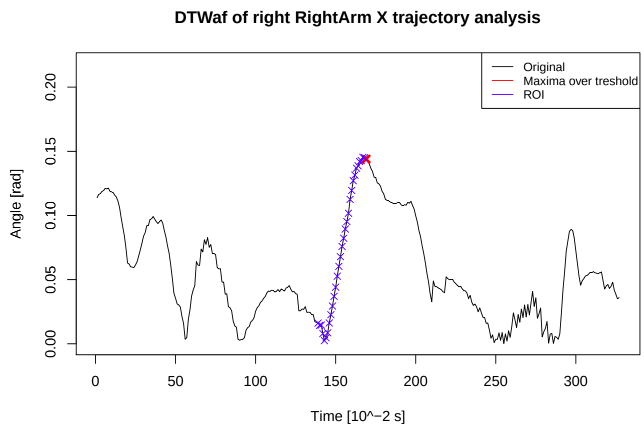
Figure 4: This figure presents plots of DTWaf of Bear hug exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.



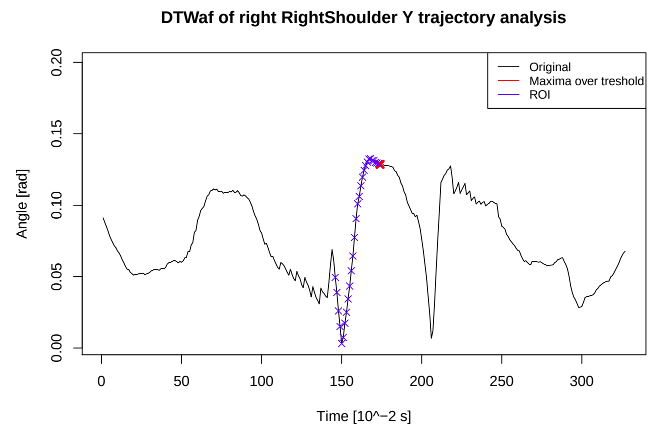
(a) $DTWaf$ of right hand



(b) $DTWaf$ of right elbow angle

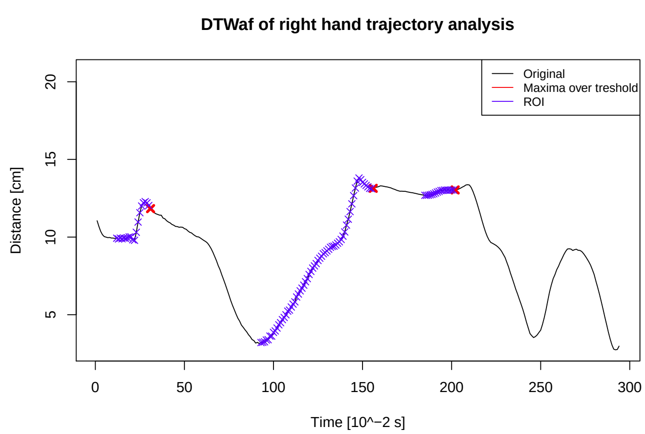


(c) $DTWaf$ of right arm rotation around X axis

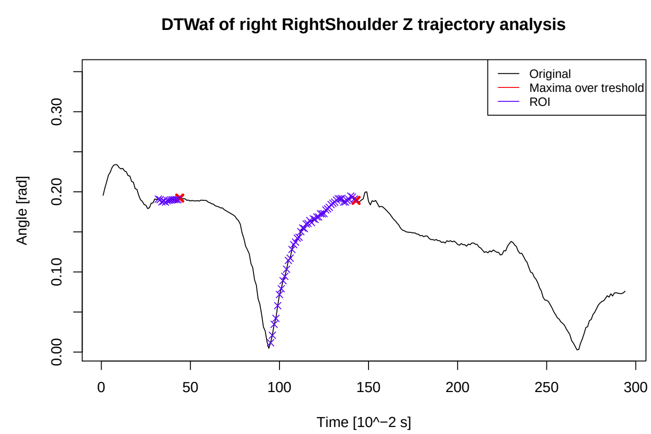


(d) $DTWaf$ of right shoulder rotation around Y axis

Figure 5: This figure presents plots of DTWaf of Dumbbells lifting exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.

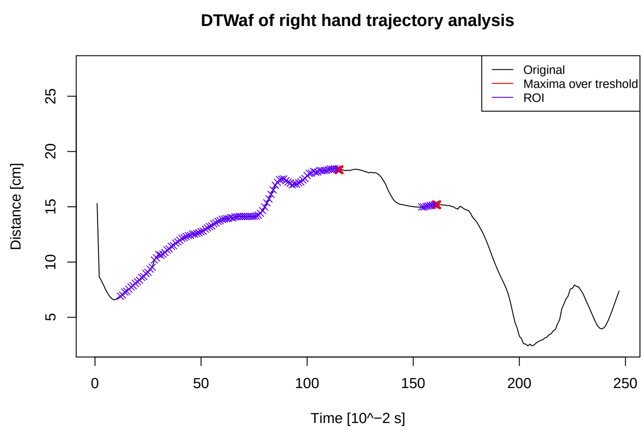


(a) $DTWaf$ of right hand

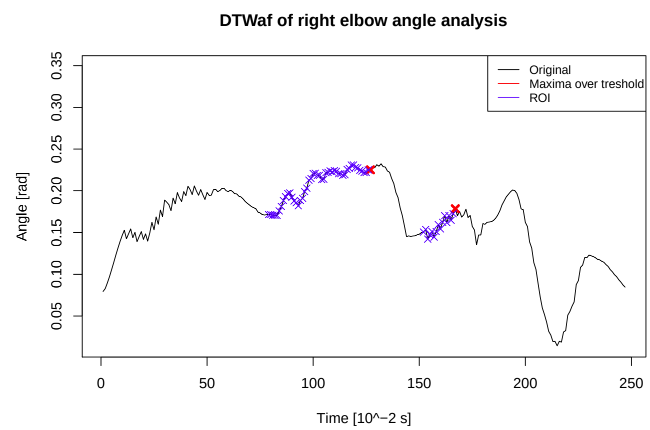


(b) $DTWaf$ of right shoulder rotation around Z axis

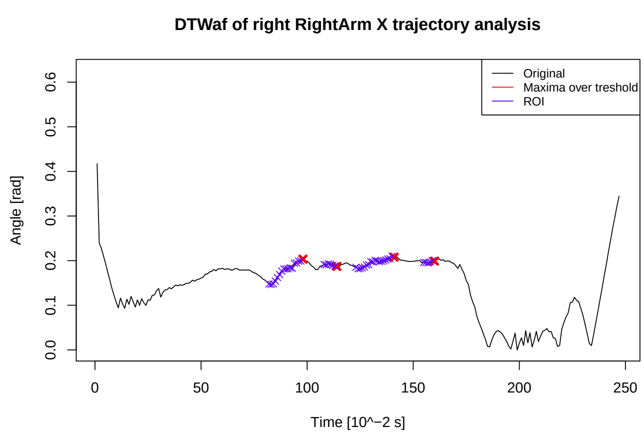
Figure 6: This figure presents plots of DTWaf of Shoulder touch exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.



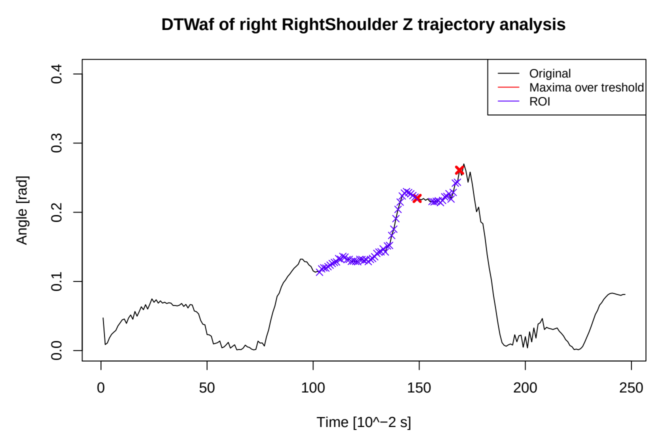
(a) $DTWaf$ of right hand



(b) $DTWaf$ of right elbow angle

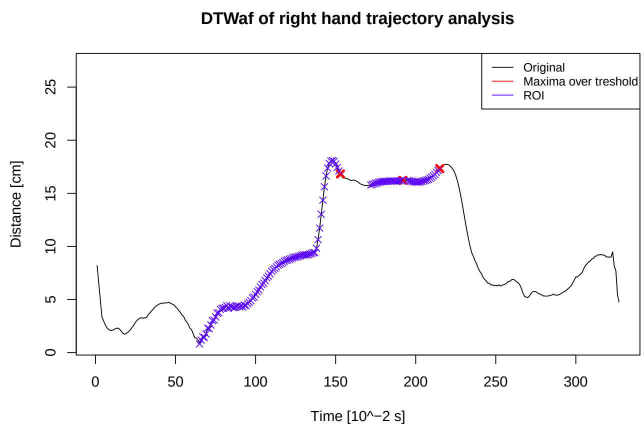


(c) $DTWaf$ of right arm rotation around X axis

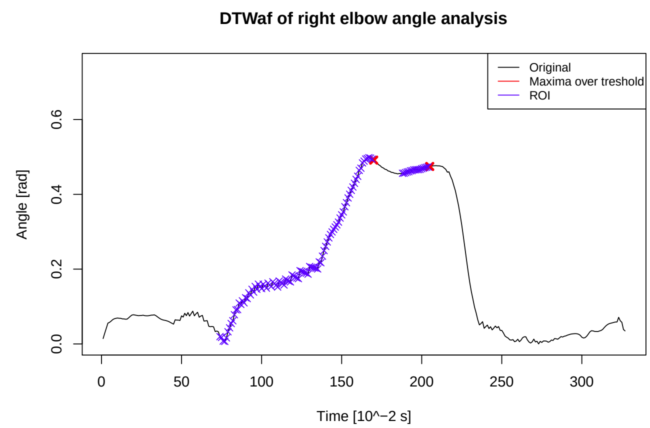


(d) $DTWaf$ of right shoulder rotation around Z axis

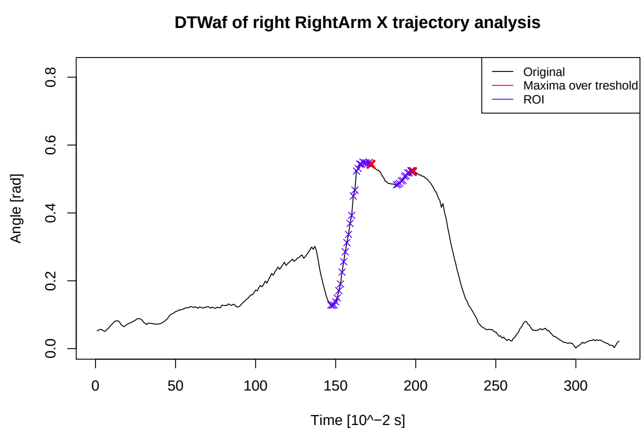
Figure 7: This figure presents plots of DTWaf of Rising arm frontally exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.



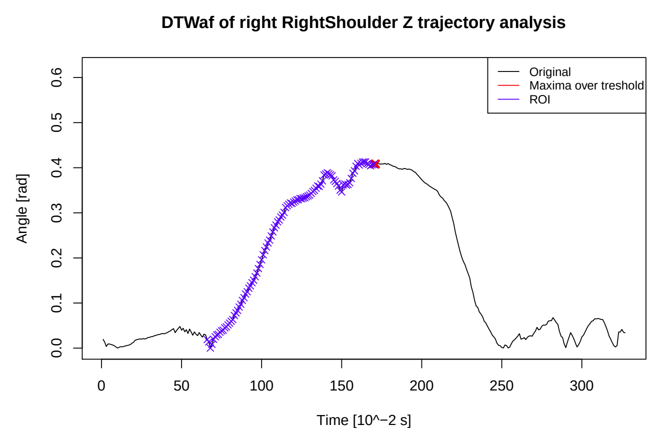
(a) $DTWaf$ of right hand



(b) $DTWaf$ of right elbow angle

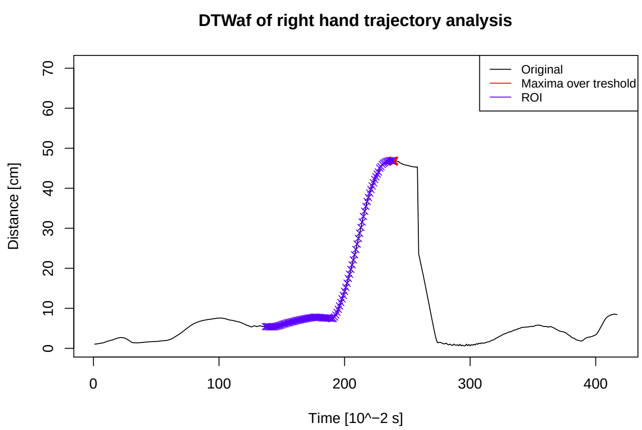


(c) $DTWaf$ of right arm rotation around X axis

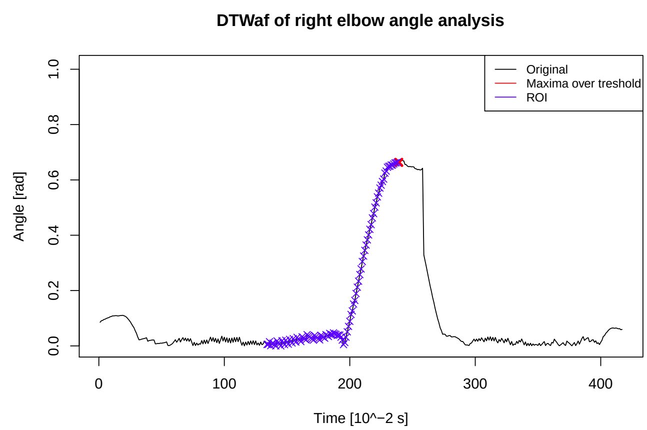


(d) $DTWaf$ of right shoulder rotation around Z axis

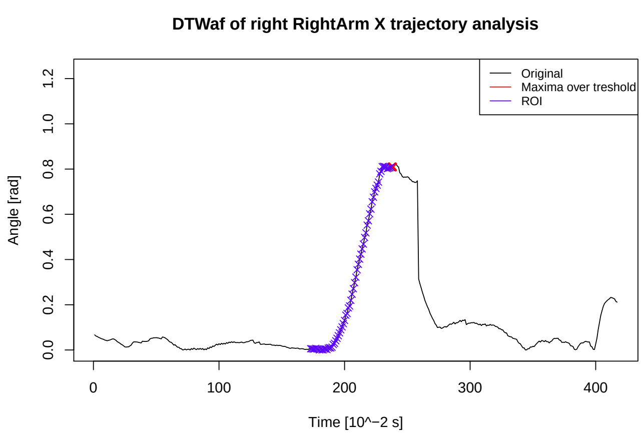
Figure 8: This figure presents plots of DTWaf of Hand between shoulders exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.



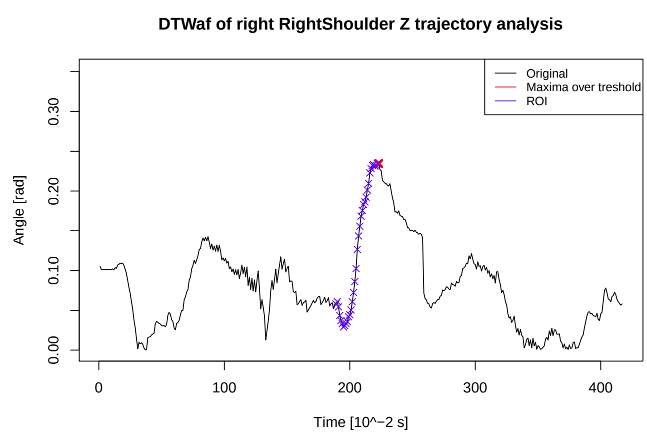
(a) $DTWaf$ of right hand



(b) $DTWaf$ of right elbow angle



(c) $DTWaf$ of right arm rotation around X axis



(d) $DTWaf$ of right shoulder rotation around Z axis

Figure 9: This figure presents plots of DTWaf of Shoulder elevation exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.

Table 3: This table presents minimal, maximal, median and mean value of DTWaf of Dumbbells lifting exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.

Feature	Min	Median	Mean	Max
Hand [cm]	1.25	5.19	8.01	28.82
ShoulderX [rad]	0.03	0.07	0.10	0.26
ShoulderY [rad]	0.00	0.06	0.07	0.13
ArmX [rad]	0.00	0.04	0.06	0.15
ArmY [rad]	0.00	0.04	0.05	0.15
ArmZ [rad]	0.00	0.05	0.24	2.78
Elbow [rad]	0.00	0.05	0.09	0.36

Table 4: This table presents minimal, maximal, median and mean value of DTWaf of Shoulder touch exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.

Feature	Min	Median	Mean	Max
Hand [cm]	2.741	9.68	9.14	13.80
ShoulderX [rad]	0.07	0.12	0.12	0.14
ShoulderY [rad]	0.00	0.05	0.05	0.10
ShoulderZ [rad]	0.00	0.15	0.14	0.23

Table 5: This table presents minimal, maximal, median and mean value of DTWaf of Rising arm frontally exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.

Feature	Min	Median	Mean	Max
Hand [cm]	2.42	13.60	12.02	18.44
ShoulderX [rad]	0.00	0.03	0.03	0.11
ShoulderY [rad]	0.00	0.03	0.03	0.11
ShoulderZ [rad]	0.00	0.07	0.09	0.27
ArmX [rad]	0.00	0.17	0.14	0.42
ArmY [rad]	0.00	0.17	0.14	0.42
ArmZ [rad]	0.00	0.16	0.17	0.37
Elbow [rad]	0.01	0.17	0.16	0.2

Table 6: This table presents minimal, maximal, median and mean value of DTWaf of Hand between shoulders exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.

Feature	Min	Median	Mean	Max
Hand [cm]	0.82	6.90	8.67	18.08
ShoulderX [rad]	0.00	0.03	0.09	0.22
ShoulderY [rad]	0.00	0.03	0.09	0.22
ShoulderZ [rad]	0.00	0.06	0.16	0.41
ArmX [rad]	0.00	0.12	0.19	0.55
ArmY [rad]	0.00	0.08	0.11	0.37
Elbow [rad]	0.00	0.08	0.17	0.50

Table 7: This table presents minimal, maximal, median and mean value of DTWaf of Shoulder elevation exercise. I present only those DTWaf in which local maxima satisfies conditions described in Section 2 B are detected.

Feature	Min	Median	Mean	Max
Hand [cm]	0.61	5.45	9.56	46.94
ShoulderX [rad]	0.00	0.03	0.03	0.11
ShoulderY [rad]	0.00	0.02	0.03	0.11
ShoulderZ [rad]	0.00	0.07	0.08	0.23
ArmX [rad]	0.00	0.04	0.13	0.82
ArmY [rad]	0.00	0.04	0.13	0.82
Elbow [rad]	0.00	0.02	0.10	0.67

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