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Computer – aided method for lower limbs kinematic analysis

Abstract. *The aim of this paper is to propose a novel method that enables kinematic analysis of motion capture (MoCap) data of lower limbs activities by comparison of body joints trajectories to the reference template. We propose an appropriate human body kinematic model, MoCap aligning procedure and heuristic evaluation with Dynamic Time Warping (DTW) - based approach. In contrast to other state-of-the-art papers, where analysis is performed on the single joint on the selected two-dimensional plane, we performed three-dimensional evaluation of human body by analyzing the whole kinematic chain jointly. This approach allows us to find which body joints affected the difference between the input and reference recordings the most. This is valuable information that a person who evaluates MoCap data expects to find. We have also performed kinematic analysis applying commonly used kinematic parameters proposed in state-of-the-art researches in order to show that in our case, when there is no restriction on speed or dynamic of action to be analyzed, those parameters cannot be used to draw valuable conclusions. We have tested our method on a dataset consisting recordings of four karate athletes with various experience in Shorin Ryu karate school. While comparing our algorithm's results to experts evaluation the true positive rate equals* 0.93 *while negative rate* 0.96.

Streszczenie. *W pracy zaproponowano nową metodę analizy kinematyki kończyn dolnych przy pomocy nagrań motion capture (MoCap). Zaproponowane rozwiązanie pozwala na kompleksową analizę całości łańcucha kinematycznego. Przetestowaliśmy zaproponowany algorytm na zbiorze danych zawierającym nagrania czterech zawodników Shorin Ryu karate uzyskując zadawalające wyniki w porównaniu do analogicznej ewaluacji przeprowadzonej przez eksperta.* ***(Komputerowa metoda analizy kinematyki kończyn dolnych)***

Keywords: Human actions analysis,Dynamic Time Warping, heuristic, kinematic chain, karate
Słowa kluczowe: Analiza ruchu, Dynamic Time Warping, heurystyka, łańcuch kinematyczny, karate

Introduction

Modern motion capture technology (MoCap) introduced human actions evaluation to many fields of everyday life. It is mostly used in rehabilitation and computer – aided sport training process. The aim of kinematic analysis is to find the most important kinematic parameters of actions that influence analyzed motions the most. Values of those parameters often undergo further processing to determine their average (typical) or optimal (best) values that refers to average or best performance. For example in MoCap-aided rehabilitation [1] the deviation from average values of kinematic parameters calculated among healthy subjects means that the analyzed person has some motion abnormality [2][3]. MoCap – aided sport kinematic analysis is often supported with kinetic analysis. In that case sportsmen want to maximize the force that is associated with most crucial activity in the discipline (for example strength of the fists strike or kick). The force associated with an action is of course the result of the kinematic of the whole body [4].

However during process of rehabilitation or training derivatives of body displacement do not always play most important role in actions analysis. In some cases we want to analyze the correctness of actions defined as similarity of joints spatial trajectory.

By a spatial trajectory we mean time-varying positions of a body joint in three-dimensional space.

Persons taking part in the exercise should not only be capable to perform it with adequate speed but, which might be in some case more important, to engage in action certain body joints [5]. In that case while performing kinematic analysis we need to evaluate spatial coordinates of joints trajectories in the kinematic chain. The direct comparison of kinematic parameters that is typically used in state-of-the-art researches like velocity, acceleration etc. might be misleading and results in incorrect conclusions.

The aim of this paper is to propose a novel method that enables kinematic analysis of lower limbs activities. We have concentrated this research on lower body, because leg kinematic is crucial for correct gait. Also leg techniques in martial art sports are very challenging even for experienced athletes because they require suppleness and good body balance. Computer – aided support might be a valuable tool that helps in development of those techniques. The heuristic to analyze MoCap data we will propose in thus paper is based on comparison of body joints trajectories of a MoCap data that we want to analyze (an input data) to the reference template MoCap data [6][7]. The method of template selection depends on the goal of the MoCap analysis.

- In case when we want to evaluate how analyzed recording differs from averaged performance of some motion, the template should be generated by a motion averaging method. To average MoCap we can use for example barycenter averaging (DBA) - based approach [15].
- Alternatively we might have MoCap data about which we already know that can be treated as reference ("ideal") and another data, that we want to compare with that reference.

Regardless of how the pattern is chosen the proposed evaluation procedure is composed of four main steps:

1. MoCap data is recalculated to appropriate kinematic model for further analysis.
2. We select a MoCap recording with a reference performance of a certain activity (see above) and the recording that we want evaluate. Both recordings are align to each other in such way that it solves problems with body different body proportions on recordings, motion directions etc.
3. A spatial trajectories of feet of input and reference data are aligned using Dynamic Time Warping (DTW) approach. A warping path that is obtained during this alignment is used to calculate so called DTW alignment function (DTWaf), that is used for further evaluation. DTWaf are also calculated for each body joint pairs in kinematic chains between reference and input image (knees, thighs and hips).
4. In the last step we compare temporal positions of DTWaf local maxima of feet with temporal positions of DTWaf local maxima of other joints in kinematic chain.

Summarizing, in order to perform MoCap analysis we propose an appropriate human body kinematic model, MoCap aligning procedure and heuristic evaluation with DTW – based approach. In contrast to other state-of-the-art papers [8][9][10][11][6][12], where analysis is performed on single body joint on selected two-dimensional plane, we performed three-dimensional evaluation of human body analyzing the whole kinematic chain jointly. This approach allows us to find which body joints affected the difference between the input and reference recordings the most. This is valuable

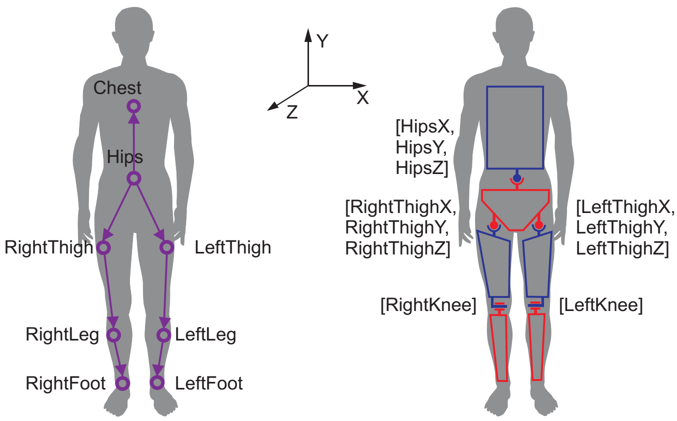


Fig. 1. Left – a hierarchical kinematic model which is an output of MoCap system, right – a kinematic model we used for action analysis.

information that a person who evaluates activities expects to find.

We have also compared results obtained by our proposed method with results from kinematic analysis in which we applied commonly used kinematic parameters proposed in state-of-the-art researches in order to show that in our case, when there is no restriction on speed or dynamic of action to be analyzed, those parameters cannot be used to draw valuable conclusions. We have published the implementation of proposed approach in R language [13]. The dataset we used in this research is also available for download [14].

Material and methods

The dataset

Our research requires the dataset that contains multiple exemplars of the same actions acquired from several persons. Because we did not find publicly available dataset that satisfies our needs we created our own using Shadow 2.0 MoCap system. This system has 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. We have already successfully used this hardware in our previous researches [15][16] and now we also use the same data acquisition protocol and software as before. Data measured by inertial sensors of our costume is processed by the software provided by hardware manufacturer to calculate mentioned above MoCap signals values according to hierarchical model in Figure 1. Each body joint of the model holds information about local rotations (orientation) of the so called "bone" attached to it, relatively to parent joint. The root (Hips) joint holds information about global rotation of the whole body. Those rotations are measured in Euler angles (this is the standard output format of the software).
Our dataset is consisted of recordings of four karate athletes with varied experience in Shorin Ryu karate school. Three of them are karate students with brown belts awarded national titles in various tournaments. The forth one is a karate master, 3-th Dan with over 25 years experience, the world champion of kata. All of them have performed four types of kicks: mawashi geri (roundhouse kick), mae geri (front kick), yoko geri (side kick) and hiza geri (knee strike) with both left and right leg. They all did 10 repetitions of those actions, so we have together $4 \cdot 4 \cdot 2 \cdot 10 = 320$ motion samples. All of them were asked to perform those actions as the training demonstration: it should be performed technically correctly, without taking an aim (they were kicking the air, not a punching bag) in the way as if they were demonstrating those actions to somebody for training issues.
Our hierarchical kinematic model uses seven IMU sensors placed over a body. It can be seen in Figure 1 (left). The joints hierarchy goes: $Hips \rightarrow RightThigh \rightarrow RightKeg \rightarrow RightFoot, Hips \rightarrow LeftThigh \rightarrow LeftKeg \rightarrow LeftFoot$ and $Hips \rightarrow Chest$. The foot position is measure with IMU sensor that is placed on the dorsal surface of foot.
We measure their acceleration and by numerical differentiation we can calculate velocities and sensors displacements (displacement is calculated as hierarchy of rotations of joints). The same joint structure is then used after recalculating hierarchical kinematic model to direct kinematic model [17]. In direct kinematic model we have coordinates of body joints in three-dimensional space. In this research we will also use a kinematic model presented in Figure 1 (right) which is an adaptation of the well - known model presented for example in [18][19][20]. The second model contains five body joints which coordinates are calculated using three-dimensional coordinates of direct kinematic model we already mentioned. All angles we measure are angles on the plane between two vectors. They can be calculated for example as arc cosine of dot product of normalized vectors. They are calculated using equations (1) – (5).
At first we calculate the rotation vector designated by Chest and Hips coordinates. To calculate those angles we use global Cartesian coordinates frame.

$$(1)\quad \begin{aligned} HipsX &\leftarrow \measuredangle([0,1,0], \overrightarrow{Chest - Hips}) \\ HipsY &\leftarrow \measuredangle([0,0,1], \overrightarrow{Chest - Hips}) \\ HipsZ &\leftarrow \measuredangle([1,0,0], \overrightarrow{Chest - Hips}) \end{aligned}$$

Than we calculate the thigh joints angles. In order to do so we first define the coordinate frame with versos:

$$(2)\quad \begin{aligned} \overrightarrow{Xt} &\leftarrow \frac{\overrightarrow{RightThigh - LeftThigh}}{\left\|\overrightarrow{RightThigh - LeftThigh}\right\|} \\ \overrightarrow{Zt} &\leftarrow \frac{\overrightarrow{Xt} - [0,1,0]}{\left\|\overrightarrow{Xt} - [0,1,0]\right\|} \\ \overrightarrow{Yt} &\leftarrow \frac{\overrightarrow{Xt} \times \overrightarrow{Zt}}{\left\|\overrightarrow{Xt} \times \overrightarrow{Zt}\right\|} \end{aligned}$$

Where $\times$ is a cross product operator and $\left\|\overrightarrow{Q}\right\|$ is a length of vector $\overrightarrow{Q}$.
Analogically, we calculate Hips angles:

$$(3)\quad \begin{aligned} RightThighX &\leftarrow \measuredangle(\overrightarrow{Yt}, \overrightarrow{RightThigh - RightLeg}) \\ RightThighY &\leftarrow \measuredangle(\overrightarrow{Zt}, \overrightarrow{RightThigh - RightLeg}) \\ RightThighZ &\leftarrow \measuredangle(\overrightarrow{Xt}, \overrightarrow{RightThigh - RightLeg}) \end{aligned}$$

and:

$$(4)\quad \begin{aligned} LeftThighX &\leftarrow \measuredangle(\overrightarrow{Yt}, \overrightarrow{LeftThigh - LeftLeg}) \\ LeftThighY &\leftarrow \measuredangle(\overrightarrow{Zt}, \overrightarrow{LeftThigh - LeftLeg}) \\ LeftThighZ &\leftarrow \measuredangle(\overrightarrow{Xt}, \overrightarrow{LeftThigh - LeftLeg}) \end{aligned}$$

The knee motion is constrained to single plane:

$$
(5)\quad \begin{aligned} RightKnee \leftarrow \measuredangle(&\overrightarrow{RightLeg - RightThigh}, \\ &\overrightarrow{RightLeg - RightFoot}) \\ LeftKnee \leftarrow \measuredangle(&\overrightarrow{LeftLeg - LeftThigh}, \\ &\overrightarrow{LeftLeg - LeftFoot}) \end{aligned}
$$

A knee joint can be considered hinge joint, so in our kinematic model we measure the knee flexion using single angle on the plane. The normal vector of this plane for the right knee is a cross product of vectors $\overrightarrow{RightLeg - RightThigh}$ and $\overrightarrow{RightLeg - RightFoot}$. The normal vector of this plane for the right knee is a cross product of vectors $\overrightarrow{LeftLeg - LeftThigh}$ and $\overrightarrow{LeftLeg - LeftFoot}$.

Data evaluation using state-of-the-art kinematic features

We have selected the set of kinematic parameters that are often chosen by researchers [21][22][23]. Those are:

- time of motion (MovementTime),
- foot trajectory length (FootTrajectory)
- maximal foot linear velocity (FootVMax),
- maximal foot linear acceleration (FootAMax),
- maximal angle of knee (LeftKneeMax),
- minimal angle of knee (LeftKneeMin),
- knee range of motion that equals $max(LeftKneeMax) - min(LeftKnee)$ that is maximum value of knee angle minus minimum value of knee angle (LeftKneeROM),
- maximal knee linear velocity (FootVMax).

Those values except the first one are calculated for left and right leg.

Commonly in actions analysis procedure the averages and standard deviations values of those parameters are calculated in order to generate a reference set. In order to evaluate a new input MoCap data one compares input kinematic parameters with those from reference set to find the potential deviations and then to interpret them. This approach is applicable only if there are some statistically observable differences between persons with different motion capabilities (for example experience level in sport or motion capability of rehabilitated person might cause various levels of motion capabilities). In the this research we will check if analysis of variance (one-way ANOVA) gives a significant results and then if there are statistical differences between pairs of persons taking part in the experiment using Tukey Honest Significant Differences. We will compare means of the features we introduced in this section between each person in our dataset in order to find if they are good indicators of how well the technique is performed. If it is so there should be some statistically observable differences between techniques performer by more skilled athletes than those performed by less skilled.

Advanced data analysis: preprocessing - MoCap alignment

In the situation when we are dealing with body action which goal is not to obtain maximal impact and speed but rather to demonstrate the correct form of motion it seems reasonable to deeply analyze trajectory of body joints that take part in it. For example in [24] authors described they pilot study on the characterization of the foot motion trajectories of different variations of the Mawashi Geri kick. The research showed that the displaying of the trajectory's shapes makes it possible to show differences between different schools techniques. As the foot position is an effect of work of kinematic chain of lower body (see Figure 1) it seems to be a good entry point for analysis of whole lower body action. In the following section we will describe our framework that analysis foot trajectory and then by applying proper heuristic model we performed advanced analysis of whole lower body motion.

The first problem we have to solve is to preprocess our dataset to the form that enables direct comparison of motions performed by a reference person (Ref) and the other one (In). The problems we have to overcome are:

- different body proportion between persons;
- motion direction correction after applying which both Ref and In persons will face the same direction at the beginning of an action;
- calculation of a global body translation (it is not provided by IMU sensors).

Proposed solutions to all of those problems will be explained in following subsections.

Body proportions

If we need to evaluate only kinematic of human data without taking into account various body proportion we need to replace the *In* body proportions with one from *Ref* dataset. This operation is instant in hierarchical kinematic model because motion there except the root joint is described only by rotation data of all other joints. After the replacement, already mentioned transformation from [17] can be applied to calculate spatial coordinates of tracked person.

Direction correction of a recorded person

In order to compare two MoCap recordings we also need to align them in that way, that initially both In and Ref persons will face the same direction. We can model this alignment in the following way: Let us assume that recordings will be rotated around *Y* (vertical) axis and the root (*Hips*) joints coordinates are identical and equals zero. If we are dealing with an activity performed with the right foot, the left foot remains stationary. Let us define vectors:

$$
(6)\quad \begin{aligned} \overrightarrow{V1} \leftarrow [&In.LeftFootX[1] - In.HipsX[1], 0, \\ &In.LeftFootZ[1] - In.HipsZ[1]] \\ \overrightarrow{V2} \leftarrow [&Ref.LeftFootX[1] - Ref.HipsX[1], 0, \\ &Ref.LeftFootZ[1] - Ref.HipsZ[1]] \end{aligned}
$$

Where $In.LeftFootX[1]$ is initial X coordinate of left foot joint of In MoCap.

If activity is performed with the left foot the right foot remains stationary and $\overrightarrow{V1}$ and $\overrightarrow{V2}$ vectors become:

$$
(7)\quad \begin{aligned} \overrightarrow{V1} \leftarrow [&In.RightFootX[1] - In.HipsX[1], 0, \\ &In.RightFootZ[1] - In.HipsZ[1]] \\ \overrightarrow{V2} \leftarrow [&Ref.RightFootX[1] - Ref.HipsX[1], 0, \\ &Ref.RightFootZ[1] - Ref.HipsZ[1]] \end{aligned}
$$

Of course $In.Hips = Ref.Hips = [0, 0, 0]$, however we left it in this equation to make vectors definition more clear for the reader.

If Hips coordinates equal $[0, 0, 0]$ two recordings are aligned if Euclidean distance between $\overrightarrow{V1}$ and $\overrightarrow{V2}$ is minimal. The rotation of point around *Y* axis where stationary point is $[0, 0, 0]$ can be computed by multiplying below matrix by a column vector with point coordinates:

$$Rot_y(\alpha) = \begin{bmatrix} cos(\alpha) & 0 & sin(\alpha) \\ 0 & 1 & 0 \\ -sin(\alpha) & 0 & cos(\alpha) \end{bmatrix} \tag{8}$$

Where α is angle of rotation.
In order to solve aligning problem we should find such α' that minimizes:

$$\min_{\alpha'}(\left|Rot_y(\alpha') \cdot \overrightarrow{V1}, \overrightarrow{V2}\right|) \tag{9}$$

Where $\left|\overrightarrow{Q}, \overrightarrow{W}\right|$ is Euclidean distance between vectors $\overrightarrow{Q}$ and $\overrightarrow{W}$. We have solved this problem using simplex method. After finding α' we need to rotate each body joint of *In* data by the α' angle.

Calculation of a global body translation

In hierarchical kinematic model all movements are described relatively to parent joint, which is the only joint that has translation data. Other joints have information about length of the body part and rotation relatively to its parent. The IMU costume measures only acceleration data and does not have direct reliable information about translation. In that case translation of root joint in hierarchical kinematic model equals zero. This situation happens also in our dataset. Because we know the relative position of IMUs we can obtain spatial (three dimensional) coordinates of tracked body relatively to root joint. We can calculate root joint translation using some heuristic, under assumption that a person does not perform sliding or jumping motions. One foot of a person has to remain stationary on the floor.
Our heuristic looks as follows: we compute position of each body joint in such a way, that stationary foot's translation would equal zero (the initial position of foot remain unchanged during whole action) – see Listing 1.

Listing 1: This code changes left foot translation to zero by translating the rest of the body.

```
Data: In – input MoCap signal
for a in 1:n-1 do
    diff := In.LeftFoot[a + 1] - In.LeftFoot[a];
    In.All[a+1] := In.All[a+1] - diff;
```

Where n is number of samples of *In* signal. The same approach is also applied to *Ref* data.
Then we align stationary foot of both models to be in the same position – see Listing 2.

Listing 2: This code changes body position of In person so that its left foot position is in the same point as in Ref person.

```
Data: In – input MoCap signal, Ref - reference signal
diff := In.LeftFoot[1] – Ref.LeftFoot[1];
for a in 1:n do
    In.All[a] := In.All[a] - diff;
```

Advanced data analysis: heuristic evaluation of DTW alignment function

After both reference and input recordings have undergo procedures described in previous section we can proceed with kinematic analysis. In our method at first we calculate DTW between feet of In and Ref MoCaps. Let us denote vectors of are three dimensional coordinates of feet as *Ref.Foot* and *In.Foot* respectively. We use body proportions of reference person to calculate spatial coordinates for both Ref and In data. As the similarity measure we take Euclidean distance.

$$[refpath, inpath] := DTW(Ref.Foot, In.Foot) \tag{10}$$

Where *refpath* is warping path vector of *Ref.Foot* onto *In.Foot* and *inpath* is warping path vector of *In.Foot* onto *Ref.Foot*. *refpath* warping path vector has length of the warping path and contains indices of *Ref.Foot* while *inpath* warping path vector has length of the warping path and holds indices of *In.Foot*. If for example first three values of *Ref.Foot* have been warped onto first value of *In.Foot* and then $4, 5$ and 6 value of *Ref.Foot* have been warped onto $2, 3$ and 4 value of *In.Foot* the *refpath* would be: $[1, 2, 3, 4, 5, 6]$ while *inpath* would be $[1, 1, 1, 2, 3, 4]$.

In the next step we generate sampled values of DTW alignment function (DTWaf) that show maximal distances in alignment of *Ref.Foot* onto *In.Foot*. Number of samples of DTWaf equal number of samples of *In.Foot*. The following pseudocode explains this procedure (see Algorithm 1).

The obtained samples of DTWaf are then smoothed with Gaussian low pass filter and we find local maxima in it. Literature reports applying Butterworth or other low-pass filters [25][26] for MoCap data filtration however in our case we do not want to introduce the group delay factor. The size of Gaussian function kernel was set to one tenth ($smoothSize = 0.1$) of the DTWaf vector length.

$$DTWaf\_smooth = DTWaf \bigotimes G_{0.1} \tag{11}$$

Local maximum is detected in smoothed signal sample on position *a* when first derivate computed with central difference schema in this sample has positive value and first derivate computed with central difference schema in sample *a+1* has negative vale:

$$\begin{gathered} \frac{DTWaf_{smooth}[a+1] - DTWaf_{smooth}[a-1]}{2}) > 0 \\ and \\ \frac{DTWaf\_smooth[a+2] - DTWaf\_smooth[a]}{2} < 0 \end{gathered} \tag{12}$$

Because we are using the discrete smoothing of finite signal we exclude from the derivative analysis tail region of the filtered data. By tail region we mean ranges of the input signal where convolution kernel references outside the input signal.

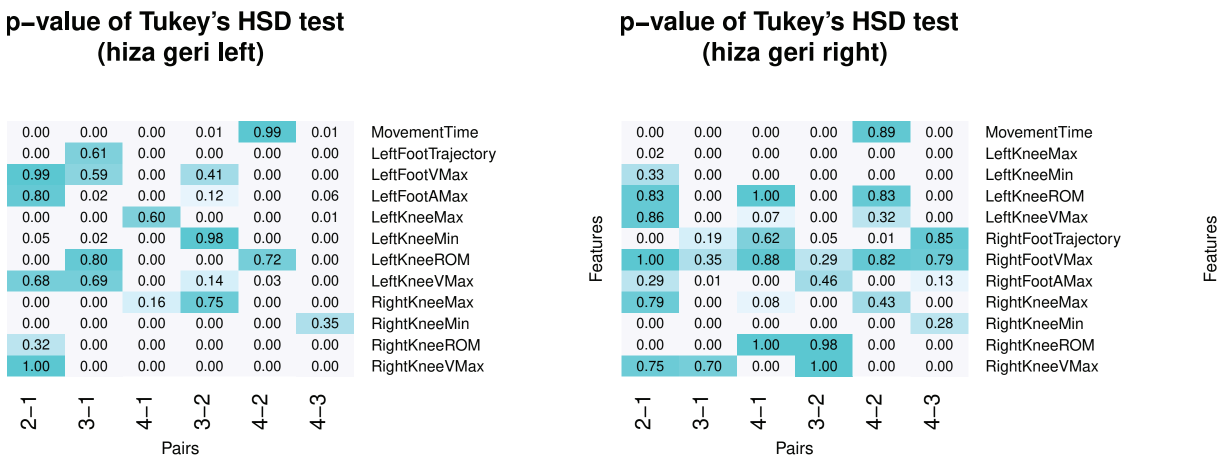
In the next step maxima found in $DTWaf\_smooth$ are thresholded with threshold value *extremumtreshold*. We left only those maxima a that satisfy the condition:

$$\begin{gathered} DTWaf_{smooth}[a] - min(DTWaf_{smooth}) \geqslant \\ (max(DTWaf_{smooth}) - min(DTWaf_{smooth})) \\ \cdot extremumtreshold \end{gathered} \tag{13}$$

extremumtreshold had values from the range 0 to 1. The appropriate value of this threshold parameter will be later evaluated by ROC characteristic on our dataset. Detected

Algorithm 1: DTWaf generation.

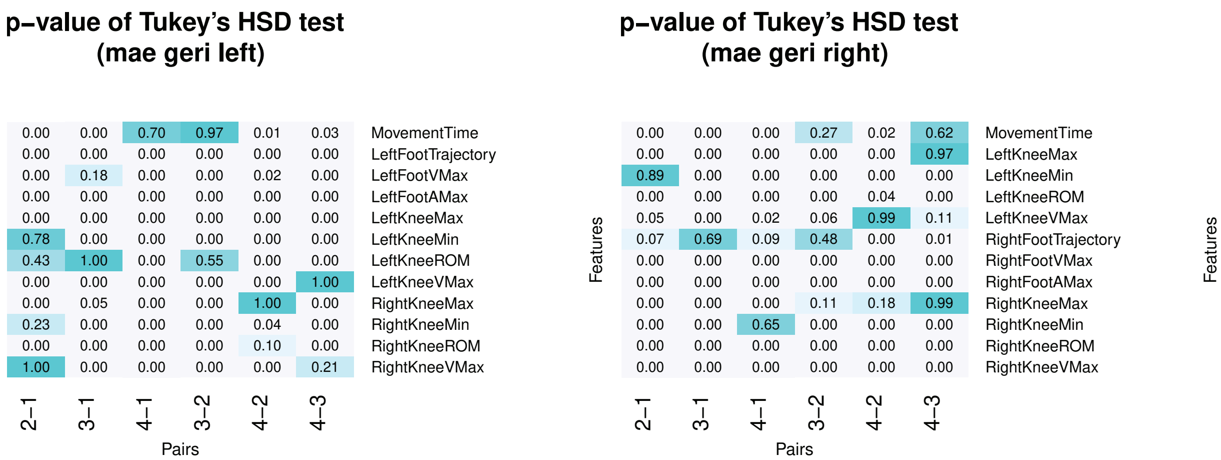
```
Data: FUN is an Euclidean distance.
Result: DTWaf
id := 1 ;                                      // index of a signal sample in input signal
idprev := -1 ;                        // previous index of signal sample in input signal
// go through all samples or a warping path vector
for a in 1:length(refpath) do
    id := inpath[a];                   // get actual index of input signal warping path vector
    value_ref := refsignal [refpath [a]] ;                   // get value of reference signal
    value_in := insignal [inpath [a]];                           // get value of input signal
    // assign distance function value between value_ref and value_in to the DTWaf
    // if there is more than one value on inpath that corresponds
    // to value on refpath assigns the maximal distance value
    if id != idprev then
        DTWaf[id] := FUN(value_ref, value_in)
    else
        DTWaf[id] := max(DTWaf[[iddprev]], FUN(value_ref, value_in))
    idprev := id
return DTWaf
```



(a) Left kick

(b) Right kick

Fig. 2. Results of Tukey's post hoc pairwise comparison test for hiza geri.

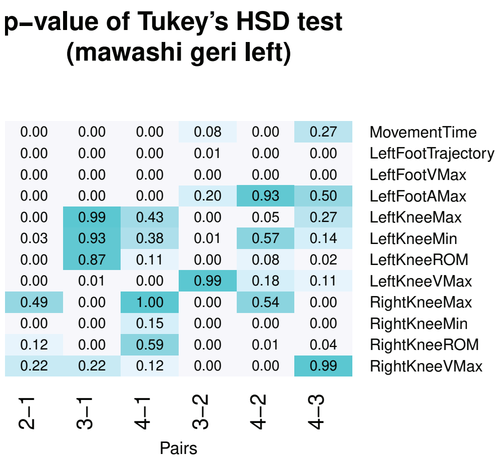


(a) Left kick

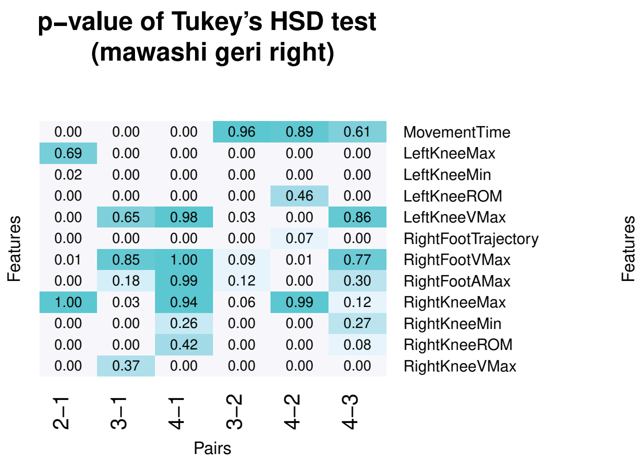
(b) Right kick

Fig. 3. Results of Tukey's post hoc pairwise comparison test for mae geri.

extrema indicate the highest local differences between reference and input data. We can use those maxima to determine what are sources of those differences. By sources we mean parts of body movements that influenced those changes the most. We propose to solve this problem using following heuristic. At first we apply *Algorithm 1* to generate

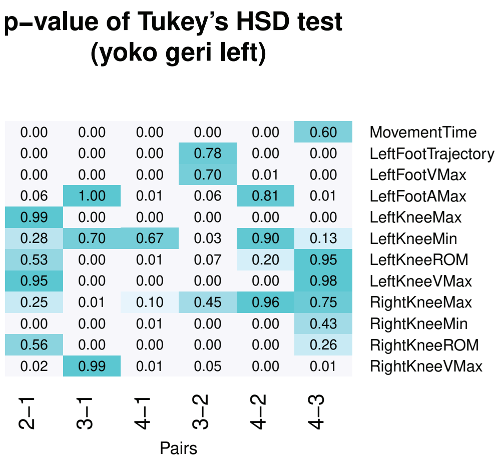


(a) Left kick

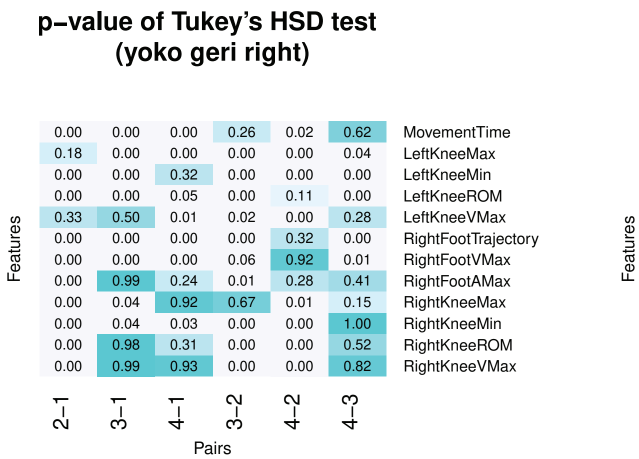


(b) Right kick

Fig. 4. Results of Tukey's post hoc pairwise comparison test for mawashi geri.



(a) Left kick



(b) Right kick

Fig. 5. Results of Tukey's post hoc pairwise comparison test for yoko geri.

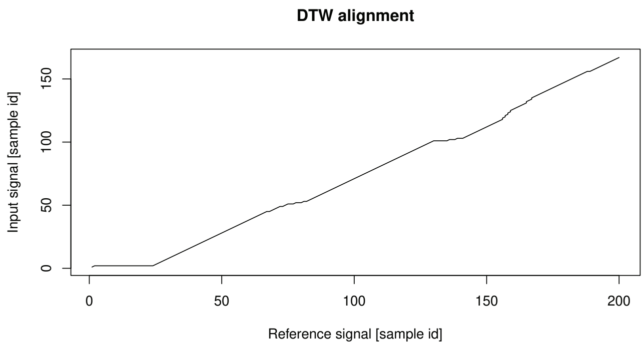


Fig. 6. An example DTW alignment of three-dimensional trajectories (reference and input data) of mawashi geri kick with the right foot.

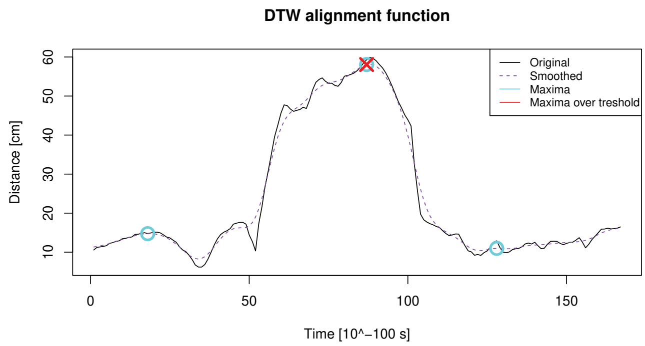


Fig. 7. An example DTW alignment function plot with smoothed data and detected local maxima of mawashi geri kick with the right foot.

DTWaf for hips, thighs and knees (left or right respectively – depending on analyzed foot) between reference and input data; however this time we will use DTW paths for foot that was previously calculated. We do it this way because we want to have same alignment of data samples on all DTWaf functions. Next we will detect local maxima and threshold data with the same schema as we did before.

In the last step we will remain only those maxima that are temporarily close to maxima detected on DTWaf of foot. We estimate the threshold of this closeness as plus / minus:

$$analyzerange := ceiling(m \cdot smoothSize) \quad (14)$$

Where m is number of samples of *inpath* signal. That is because maximal displacement of corresponding maximums on DTWaf is proportional to the length of the signal and the size of the smoothing kernel. It is more informative for the person that analyze the results of our algorithm to see not only the MoCap samples in which local maximums of *DT-*

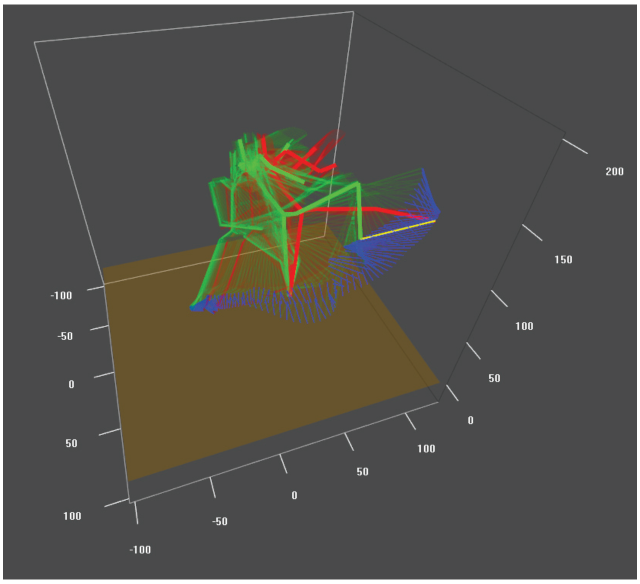


Fig. 8. Rendering of 3D MoCap data with DTW alignment marked as blue line of mawashi geri kick with the right foot. Yellow line indicates the local maximum over threshold. Reference data is green and input data is red. Units on the axis are cm.

Waf were detected but rather range of samples that contains parts of actions that resulted in presence of those extrema. We define those regions of interest as all data samples that happened earlier than detected maximum and in which first derivate has positive value. We find those samples in iterative process, starting from detected maximum and going backwards through samples until we find first one with a negative derivate – see Listing 3.

Listing 3: Extrema ROI detection

```
Data: In – input MoCap signal, Ref - reference signal
a := maximum_index;
ROI := emty;
while a ⩾ 1 and derivate[a] ⩾ 0 do
    ROI add a;
    a = a - 1;
Return ROI;
```

Our approach presented in this section is a complete heuristic that allows to compare two MoCap recordings and to indicate on kinematic model (Figure 1 right) which body joints and in which parts of action affect the differences between those recordings the most. As we mentioned before, instead of using a single reference recording we can use averaged MoCap data from many repetitions of the same action [15]. Using averaged data as the reference makes data analysis less sensitive to the random errors that might happened during MoCap session. In the next section we will present evaluation of our algorithm on the dataset we have described previously.

Statistical analysis of kinematic parameters

At first we have calculated mean and standard deviations of kinematic parameters introduced in section "Data evaluation using state-of-the-art kinematic features" - they are presented in Tables $1-4$.

There is not much sense in evaluation a large sample of people in each skill level jointly, especially when they are below master (black belt) level. There are a number of technical inaccuracies that are made before obtaining certain skill level and taking more and more athletes of that type will certainly resulted in high variation of calculated features. Due to this fact each person is compared separately to a most experienced athlete.

We have performed one-way ANOVA in order to check if there is a (statistically) significant difference in values of kinematic features presented in section "Data evaluation using state-of-the-art kinematic features" between experiment participants with various skill levels while they are performing four types of karate kicks. Groups we are comparing in this experiment are particular persons taking part in experiment and we compare each motion and each feature separately. To determine which group is different from the others post hoc test is performed namely Tukey Honest Significant Differences test. We did it in order to compare pair means. The aim of this experiment is to check, if there is a group of kinematic parameters (or a single one) that differs significantly between each other and especially is there is a significant difference between less skilled sportsmen and most skilled one. If it so, this group of features distinguish people with various skilled level and might indicate how certain type of motion is performed by more proficient person. The most experienced person in this experiment was the fourth one; we will also call it a reference person.

We have used ANOVA test in order to check if the variations between mean values person and technique of examined parameters are due to differences inside the populations. In all examined cases the p-value was below 0.05. Due to this we accept the hypothesis that there is a significant relationship between each of those parameters and the person who performed an action. In order to detect which groups are statistically different from each other we performed a Tukey's post hoc pairwise comparison test. The results of this test are presented in Figures $2-5$. Figures have color – coded cells with p - value. The p value > 0.05 indicated by intensive cyan color indicates that there are no significant differences between classes (given kinematic parameter for a particular karate technique). Classes 1, 2, 3 are less experienced participants while 4 is the most experienced one.

Trajectory analysis

In this experiment we have generated the averaged MoCap from all recordings of most experienced karate master with algorithm [15] and compared those templates with all recordings of less experienced athletes. An example visualization of two aligned MoCap recordings that contains performance of mawashi geri kick can be found on Figures 6-8. In Figure 8 data samples that contain DTWaf extrema are no transparent. Blue lines shows corresponding samples from both recordings (green is reference, red is input). Yellow line joins data samples with extremal values. We asked the expert to indicate by looking on three – dimensional visualizations of aligned MoCap recordings which differences between Ref and Input data are important from the perspective of karate trainer. We have used this expert evaluation as the reference for the ROC analysis of *extremumtreshold* parameter of our method. The ROC curve is presented in Figure 9. The area under curve equals AUC = 0.94. Figure 10 presents an example DTW alignment function plots with smoothed data and detected local maxima for the same data as in Figures 6-8.

We have found optimal threshold parameter that minimizes following formulas:

$$O_1 = min_{threshold}(|sensitivity - specificity|) \quad (15)$$

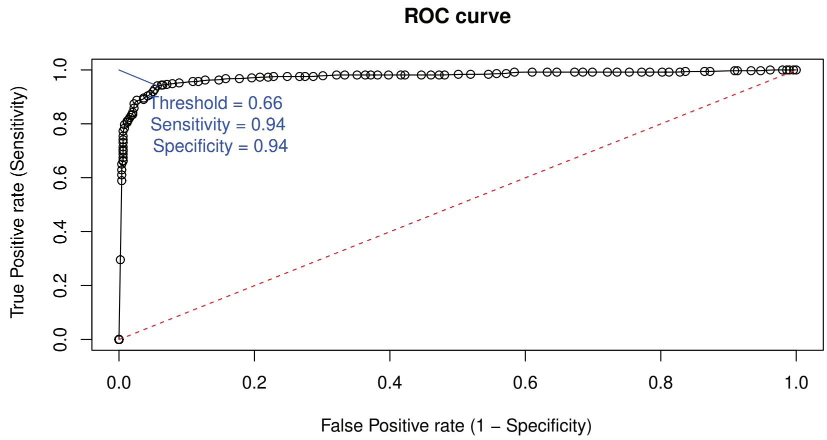
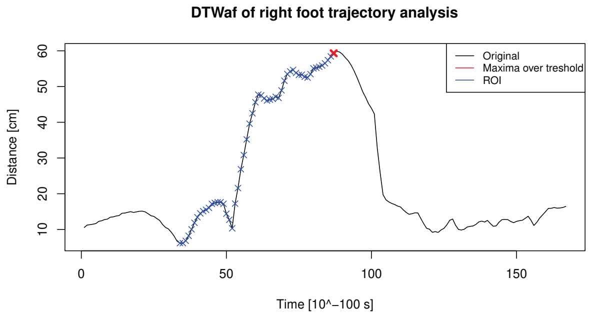
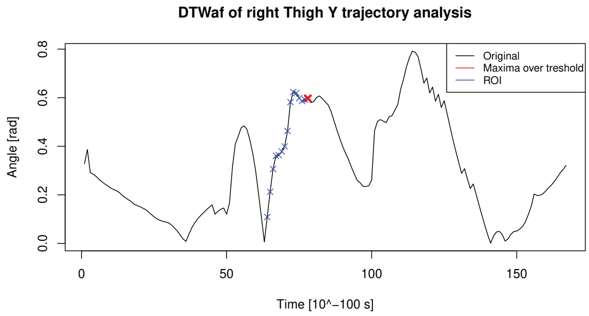


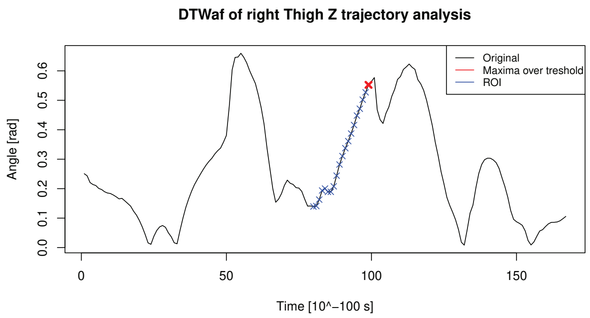
Fig. 9. ROC plot for threshold parameter.



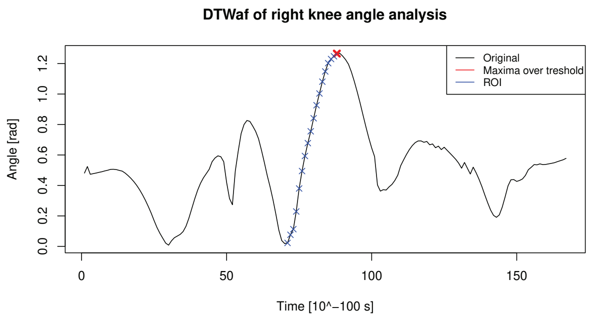
(a)



(b)



(c)



(d)

Fig. 10. An example DTW alignment function plot with smoothed data and detected local maxima for the same data as in Figures 6-8. Blue crosses are detected ROIs (see Listing 3).

Table 1. Kinematic parameters of the first person (brown belt).

	MawashiGeriL	HizaGeriL	MaeGeriL	YokoGeriL	MawashiGeriR	HizaGeriR	MaeGeriR	YokoGeriR
MovementTime[s]	1.55±0.1	1.34±0.16	1.27±0.11	1.52±0.12	1.72±0.18	1.34±0.07	1.24±0.09	1.75±0.08
LeftFootTrajectory[m]	4.43±0.11	3.57±0.12	3.72±0.06	4.26±0.21	0±0	0±0	0±0	0±0
LeftFootVMax[m/s]	6.24±0.18	5.57±0.47	6.31±0.3	5.42±0.31	0±0	0±0	0±0	0±0
LeftFootAMax[m/s^2]	1.51±0.35	1.19±0.29	1.82±0.39	1.76±0.38	0±0	0±0	0±0	0±0
LeftKneeMax[rad]	3.12±0.03	3.09±0.04	3.01±0.02	3.1±0.04	3.06±0.06	2.98±0.04	2.92±0.05	3.08±0.05
LeftKneeMin[rad]	1.11±0.11	1.34±0.06	1.17±0.05	1.13±0.12	2.43±0.08	2.36±0.04	2.38±0.04	2.59±0.07
LeftKneeROM[rad]	2.01±0.1	1.75±0.07	1.85±0.05	1.96±0.11	0.63±0.1	0.61±0.07	0.54±0.06	0.49±0.07
LeftKneeVMax[m/s]	18.31±2.8	9.42±0.86	17.36±2.42	21.91±2.53	2.64±0.64	2.98±0.36	2.66±0.54	2.74±0.75
RightFootTrajectory[m]	0±0	0±0	0±0	0±0	4.32±0.07	3.28±0.07	3.96±0.07	4.21±0.06
RightFootVMax[m/s]	0±0	0±0	0±0	0±0	6.14±0.58	5.11±0.22	6.87±0.21	5.62±0.33
RightFootAMax[m/s^2]	0±0	0±0	0±0	0±0	1.15±0.11	1.53±0.81	1.43±0.18	1.22±0.24
RightKneeMax[rad]	2.84±0.09	2.96±0.04	2.7±0.03	2.81±0.09	3.01±0.09	2.87±0.11	2.96±0.06	3.02±0.04
RightKneeMin[rad]	2.36±0.07	2.45±0.05	2.16±0.03	2.38±0.07	1.53±0.09	1.27±0.03	1.43±0.06	1.58±0.1
RightKneeROM[rad]	0.49±0.09	0.51±0.06	0.55±0.02	0.42±0.09	1.48±0.15	1.6±0.1	1.53±0.1	1.45±0.12
RightKneeVMax[m/s]	2.15±0.32	2.07±0.31	2.21±0.21	2.46±0.49	13.81±1.69	7.79±1.12	17.51±1.01	13.29±1.34

Table 2. Kinematic parameters of the second person (brown belt).

	MawashiGeriL	HizaGeriL	MaeGeriL	YokoGeriL	MawashiGeriR	HizaGeriR	MaeGeriR	YokoGeriR
MovementTime[s]	1.71±0.12	1.53±0.11	1.3±0.14	1.88±0.18	1.68±0.16	1.59±0.12	1.39±0.19	1.89±0.17
LeftFootTrajectory[m]	4.63±0.18	3.12±0.22	3.87±0.05	4.33±0.11	0±0	0±0	0±0	0±0
LeftFootVMax[m/s]	7.26±0.49	5.91±0.64	9.82±0.37	5.73±0.77	0±0	0±0	0±0	0±0
LeftFootAMax[m/s^2]	1.96±0.41	1.96±1.08	4.84±0.67	2.27±0.34	0±0	0±0	0±0	0±0
LeftKneeMax[rad]	3.04±0.04	2.92±0.09	2.82±0.04	2.83±0.11	2.63±0.07	2.82±0.05	2.53±0.07	2.73±0.08
LeftKneeMin[rad]	1.26±0.1	1.36±0.09	1.02±0.07	1±0.07	1.66±0.08	1.81±0.07	1.74±0.07	1.82±0.04
LeftKneeROM[rad]	1.78±0.09	1.56±0.13	1.8±0.08	1.83±0.11	0.97±0.1	1.02±0.06	0.79±0.1	0.91±0.08
LeftKneeVMax[m/s]	18.64±2.63	8.1±1.53	29.47±1.23	16±2.49	3.92±0.74	5.49±0.8	3.22±0.59	4.31±1.36
RightFootTrajectory[m]	0±0	0±0	0±0	0±0	4.76±0.19	3.09±0.13	3.9±0.1	4.54±0.17
RightFootVMax[m/s]	0±0	0±0	0±0	0±0	8.3±0.49	6.25±0.64	9.85±0.47	6.39±0.93
RightFootAMax[m/s^2]	0±0	0±0	0±0	0±0	2.19±0.45	2.13±0.62	4.61±0.5	2.19±0.68
RightKneeMax[rad]	2.6±0.16	2.99±0.09	2.54±0.07	2.87±0.11	2.92±0.09	2.49±0.15	3.02±0.07	2.99±0.08
RightKneeMin[rad]	1.78±0.08	2±0.05	1.86±0.05	2.11±0.04	1±0.12	0.91±0.13	0.71±0.1	0.97±0.07
RightKneeROM[rad]	0.82±0.17	1±0.11	0.68±0.06	0.76±0.12	1.92±0.18	1.58±0.13	2.31±0.06	2.02±0.1
RightKneeVMax[m/s]	3.71±1.31	4.66±0.62	3.25±0.37	3.22±0.5	20.98±1.43	7.84±1.64	32.44±1.76	17.57±3.45

Table 3. Kinematic parameters of the third person (brown belt).

	MawashiGeriL	HizaGeriL	MaeGeriL	YokoGeriL	MawashiGeriR	HizaGeriR	MaeGeriR	YokoGeriR
MovementTime[s]	1.82±0.18	1.36±0.1	1.44±0.08	1.97±0.17	1.78±0.16	1.31±0.12	1.49±0.17	1.98±0.14
LeftFootTrajectory[m]	3.98±0.06	2.67±0.16	3.55±0.05	3.72±0.19	0±0	0±0	0±0	0±0
LeftFootVMax[m/s]	5.11±0.46	4.38±0.47	6.7±0.2	4.49±0.59	0±0	0±0	0±0	0±0
LeftFootAMax[m/s^2]	1.65±0.35	2.86±0.99	2.82±0.36	1.59±0.36	0±0	0±0	0±0	0±0
LeftKneeMax[rad]	3.07±0.06	2.82±0.06	3.09±0.02	2.96±0.1	2.77±0.1	2.67±0.04	2.54±0.05	2.84±0.12
LeftKneeMin[rad]	1.17±0.1	1.11±0.08	0.71±0.07	1.1±0.13	2.2±0.08	2.08±0.03	1.92±0.07	2.27±0.1
LeftKneeROM[rad]	1.91±0.08	1.71±0.08	2.38±0.06	1.85±0.14	0.58±0.07	0.59±0.06	0.63±0.07	0.57±0.04
LeftKneeVMax[m/s]	15.67±3.56	11.16±1.57	29.47±0.85	15.58±2.45	4.27±1.46	2.6±0.31	2.72±0.29	5.23±1.53
RightFootTrajectory[m]	0±0	0±0	0±0	0±0	4.48±0.17	3.03±0.22	3.76±0.06	4.12±0.05
RightFootVMax[m/s]	0±0	0±0	0±0	0±0	9.15±3.89	5.66±2.65	7.68±0.32	5.42±0.27
RightFootAMax[m/s^2]	0±0	0±0	0±0	0±0	2.99±1.94	3.03±1.47	2.11±0.45	1.74±0.58
RightKneeMax[rad]	2.78±0.07	2.68±0.07	2.7±0.05	2.83±0.08	3±0.07	2.79±0.12	3.01±0.07	2.93±0.05
RightKneeMin[rad]	2.11±0.04	2.03±0.04	2.11±0.03	2.15±0.05	0.93±0.1	0.98±0.08	0.97±0.1	0.97±0.05
RightKneeROM[rad]	0.67±0.1	0.65±0.08	0.6±0.05	0.68±0.08	2.07±0.12	1.81±0.09	2.04±0.16	1.96±0.07
RightKneeVMax[m/s]	3.84±0.91	2.99±0.32	2.91±0.4	4.23±0.7	17.08±3.14	11.16±1.15	25.64±1.93	16.75±1.48

Table 4. Kinematic parameters of the fourth person (black belt, most experienced one).

	MawashiGeriL	HizaGeriL	MaeGeriL	YokoGeriL	MawashiGeriR	HizaGeriR	MaeGeriR	YokoGeriR
MovementTime[s]	2.08±0.16	1.75±0.09	1.49±0.1	2.38±0.19	2.12±0.2	1.92±0.09	1.8±0.23	2.33±0.25
LeftFootTrajectory[m]	4.94±0.15	3.01±0.23	4.09±0.07	4.87±0.08	0±0	0±0	0±0	0±0
LeftFootVMax[m/s]	9.02±0.75	5.63±0.37	9.55±0.23	7.91±0.81	0±0	0±0	0±0	0±0
LeftFootAMax[m/s^2]	3.8±0.72	0.88±0.29	3.66±0.35	2.26±0.6	0±0	0±0	0±0	0±0
LeftKneeMax[rad]	3.04±0.03	2.79±0.05	2.94±0.04	3.09±0.05	3.1±0.05	2.91±0.05	2.77±0.04	2.99±0.09
LeftKneeMin[rad]	1.24±0.08	1.26±0.05	1.14±0.06	1.05±0.08	2.32±0.05	2.32±0.06	2.36±0.04	2.32±0.05
LeftKneeROM[rad]	1.81±0.1	1.53±0.04	1.8±0.1	2.04±0.11	0.78±0.06	0.59±0.07	0.41±0.04	0.67±0.12
LeftKneeVMax[m/s]	23.02±2.28	8.76±1.24	23.8±1.47	21.33±2.09	4.44±0.93	3.16±0.31	2.07±0.48	3.61±0.56
RightFootTrajectory[m]	0±0	0±0	0±0	0±0	5.1±0.13	2.94±0.18	3.86±0.12	5.08±0.14
RightFootVMax[m/s]	0±0	0±0	0±0	0±0	9.01±0.42	5.2±0.61	9.08±0.46	7.75±0.86
RightFootAMax[m/s^2]	0±0	0±0	0±0	0±0	3.13±0.34	0.8±0.2	3.16±0.27	2.29±0.89
RightKneeMax[rad]	2.78±0.06	2.62±0.05	2.6±0.04	2.73±0.08	3.02±0.07	2.92±0.06	2.84±0.03	2.92±0.06
RightKneeMin[rad]	2.17±0.06	2.18±0.05	2.19±0.04	2.25±0.08	0.85±0.04	1.11±0.05	1.01±0.05	0.88±0.06
RightKneeROM[rad]	0.61±0.09	0.44±0.08	0.41±0.05	0.48±0.11	2.17±0.1	1.8±0.05	1.83±0.04	2.04±0.09
RightKneeVMax[m/s]	2.93±0.74	2.04±0.41	2.18±0.47	3.31±0.77	22.4±0.59	7.24±0.94	22.85±0.5	17.34±1.53

and

(16)

$$O_2 = min_{threshold}(\sqrt{(1 - sensivity)^2 + (1 - specificity)^2})$$

In both cases it is 0.66 for:
$sensitivity = 0.94$ and $specificity = 0.94$ with:
$TP = 353, FP = 28, TN = 467, FN = 22$. We have used *Algorithm 1* to all TP cases to generate*DTWaf* for hips, thigh and knee (left or right respectively – depending on analyzed foot) between reference and input data using DTW paths for foot as it was described in section "Advanced data analysis: preprocessing - MoCap alignment". We have also used Extrema ROI detection algorithm to find data samples that are relevant to detected maxima. Example DTWaf plots with detected ROI ($threshold = 0.66$) for the same data as in Figures 6-8 are in Figure 10.

Discussion

As can be seen in Tables $1 - 4$ the most experienced (the fourth) participant has performed all of these actions in longer time period than other participants. However the longest time of motion seems not to affect other parameter of motion like maximal velocity and acceleration of leg and knee which is most often higher than in case of other participants. There are some actions however when those parameters are lower than in samples of other athletes: for example second person did hiza geri and mae geri kick with left leg faster (with higher foot velocity) than the fourth person. The max, min and knee ROM angle varies between techniques and participants. The same is with length of the foot trajectory which is dependent to body proportions.

As can be seen in the results of Turkey's HSD test there is no single kinematic parameter that differs significantly between reference (most skilled) person and all other person and in the same time. Basing only on information from Tables 1-4 and Figures 2-5 we cannot state which motions features distinguish the world champion from the students. In case of yoko geri and mawashi geri techniques features values between experiment participants differ less (there are more features with p-value > 0.05) than in case mae geri kick, which is a far more easier technique. This situation happens because of two factors: there is a large values variation of these parameters and also all persons are mainly focused to perform those actions technically correctly that does not mean to perform those actions with the same (maximal) speed all the time. What is more while performing same action several times muscles fatigue appears which changes time of action execution. Because of it in this type of motion scenario, when participants are not aimed on for example having the highest impact of their kicks or to kick in the given target, but rather to demonstrate the correct performance of the technique, parameters defined in section "Data evaluation using state-of-the-art kinematic features" did not proved to be usable in action evaluation. These seems to be the prove that kinematic features from that section are not a good indicator of skills level in our scenario. Speaking colloquially, in our experiment scenario it is not true that a person who is capable to maximize or minimize parameters from that section is performing karate techniques better than other participants.

Now we will discuss results of the experiment in which we applied proposed method of motion trajectory analysis. The observation of the expert were also based on kinematic differences between skill levels, however those differences were based on comparison of body joints motions trajectories rather than motion derivatives. It can be easily explained: in case of motions, that lasts no longer than 2 seconds, human observer is often not capable to recognize velocity or acceleration of limbs, even if watching a recording in a slow motion. Also when we take into account correctness of performing certain action in the means of similarity of human joints spatial trajectory, the typical kinematic features from section "Data evaluation using state-of-the-art kinematic features" might be not only not informative as our first experiment showed, but also misleading.
We have presented visualizations of obtained results to our expert and he had agreed with the results that our heuristic has indicated. Also ROIs detected by our approach on limbs in kinematic chains were evaluated as the correct by our expert. The TPR of our method with threshold 0.66 equals 0.93 while TNR 0.96. These is quite good results however some error are still present. Our algorithm deals well with analyzes of action correctness by evaluating of similarity of human joints spatial trajectory. This makes our method useful not only for sport data but also to many other applications like for example rehabilitation.
The source of the errors were detection of maxima at the beginning (during rising the foot) and the ending part of the motion (when foot is put on the ground) what our expert found irrelevant. The obtained results have been found valuable in the process of computer aided coaching and sport data analysis.

Conclusion

Basing on discussion presented in previous section we can conclude that the proposed MoCap data evaluation model is reliable tool for finding most important differences and ROI preceding those differences in lower body kinematic chain. The trajectory analysis on relatively large dataset seems to give more applicable results than statistical analysis using popular kinematic parameters. That happens because of large variability of kinematic parameter values in our dataset (this is quite common in real world data) that makes the statistical comparison inapplicable for distinguishing more experienced athletes for less skilled. What is more our method is capable to run on data from IMU sensors which are much cheaper than video based MoCap hardware and also more mobile.

In case of grappling sports in which routines have to be trained in pairs (e.g Judo or some Aikido techniques) there is not much use in proposed approach. In case of striking sports however (kickboxing, box, muay thai) proposed methods can be applied in the same way as proposed in this paper. In case of physical activities developed during physical education classes we believe that proposed solution might be useful if pupils are mastering some well specified motion types for example tennis or baseball swings.
Among another possible application of the proposed approach (however with application of different kinematic chain) is to apply it to measure and compare the development of evaluate psychomotor skill acquisition during simulator-based training in medicine, for example transthoracic echocardiography (TTE) [27][28]. There have been several researches in this field [29][30][31] and we believe it might be a promising subject for the further research.

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