Clustering-based Human Locomotion Parameters for Motion Type Classification

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Abstract: The paper proposes a classification method of human locomotion types from video sequences based on motion parameters clustering. A set of motion parameters is semi-automatically extracted from training video sequences that contain three different types of movement: walking, jogging and running. The motion parameters (postural, frequential, and cinematic) are stored in a relational database and statistic parameters such as minimum, maximum, average and standard deviation are computed. Then a K-means clustering is applied on all the statistic parameters combinations and the results are evaluated using the purity measure to determine most significant parameters to be used in classification. Because the number of training video sequences is reduced, the proposed method may be used as a model of classification only. The automatic determination of movement parameters will increase the data collection size and real testing of the classification method.

Keywords: human locomotion, video analysis, ontology, K-means.

1. Introduction

Applications in various fields such as video games [4], dance education [18], [19], sports [3], medicine (mainly rehabilitation) [11], [21], self-driving cars and robotics [5], [6], [10], and security [1] require an improved understanding and representation of human locomotion.

Various types of human activities are categorized in: gestures, actions, interactions, and group activities [1]. Gestures are elementary movements of a body part, for example “waiving hand”. Complex activities composed from multiple gestures organized temporally are actions. Some examples of human actions are walking, running, jumping. Interaction is a human activity that involves two or more persons and/or objects. Group activities are activities that involve a group of persons and/or objects. The movements of body parts at joints are mainly rotational and take place in three reference planes: sagittal, frontal and transversal. These movements are flexion and extension (frontal axis), abduction and adduction (sagittal axis), medial and lateral (transverse axis).

Walking is a human action in which one foot touchdown is followed by the touchdown of the other foot in a continuous pattern [3]. One of the differences between walking and running is that in the running cycle for a period of time both feet are in the air [7]. Jogging is a form of running at a slower pace [15].

The type of human locomotion may be indicative for the type of activity, intentions, attitudes, circumstances perceived – e.g., dangers, and mood of the person. Consequently, the fast detection of the type and specifics of the locomotion may indicate dangerous situations, among others.

The analysis of the human movement is qualitative and quantitative. While the qualitative analysis of human movement is a non-numerically analysis and describes human actions as patterns, the quantitative analysis requires a large amount of measurements of the parameters which describe the human action and a computer to perform numerical calculation [3].

Human locomotion represents a complex kinematics, with all the body parts participating, involving a large degree of freedom. In [17], [18] and [19] the authors have proposed semantics of the human movement. A semantic representation of human motion in combination with a motion recognition algorithm for digital human simulation is presented in [16].

The combined use of fuzzy logic and complex dynamics has been advocated by several groups, for example [8], [9], [22], including in representing and classification of human movements [9], [21].

This article follows the track established by the papers [12], [13], [23]. Compared to those preliminary papers and to the literature, this article brings the following contributions: a complete statistical characterization of the movement, with the related database, including all angles between the relevant body parts, the derivation of the membership functions based on the statistics, the automatic clustering of the movement sequences in view of objective determination of the membership functions related to a more detailed analysis of the dynamics, and detection of abnormal movements applications, with relevance in the medical and security fields.

Throughout the paper, the main parameters of the human locomotion, as established in the literature, for example in [24], are taken into account. This study follows the same path by analyzing basic human locomotion and proposing a fuzzy ontology of it, based on video analysis.

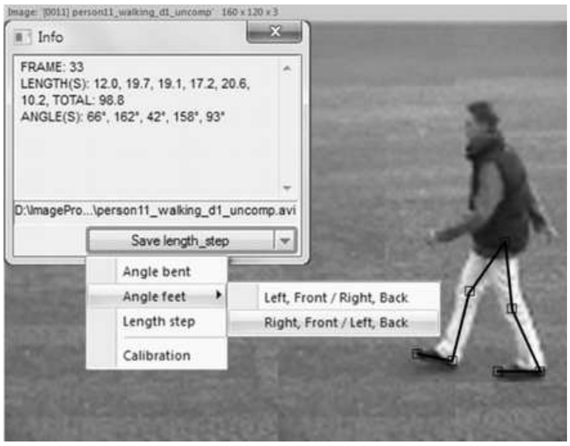
The paper organization is as follows. Section 2 presents the video database and the method used to determine the parameters of the locomotion. In Section 3 a K-means algorithm was applied on extracted parameters. In the fourth section are presented the experimental results and the last section concludes the paper.

2. Human Motion Characteristics

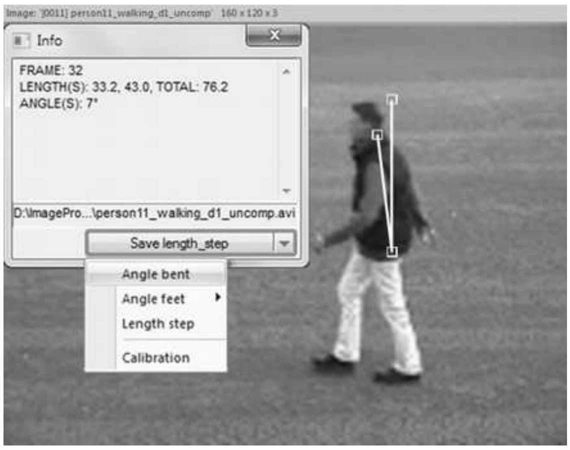
In this study, it has been used KTH video collection taken over homogeneous backgrounds with a static camera with 25fps frame rate [20], in which are performed three types of human actions: walking, jogging and running by 25 different persons. The information extracted from video sequences is the following parameters which describe the human locomotion: postural parameters (*step length*, *angles*), frequential parameter (*frequency*) and cinematic parameters (*velocity*) [12], [13].

An application was developed to facilitate the measurement of these parameters (Figure 1, Figure 2). In the application, the description points of the segments which form the angles and length are manually selected and automatically computed. The measurements are stored in a database (Figure 2). Based on the values of these measurements a statistic is generated. The minimum, maximum, average and standard deviation for all measurement for the first ten subjects from KTH video collection

(a)



(b)



(c)

Figure 1. Parameters capture: (a) *step length*, (b) *feet angles*, (c) *bent angle*.

who perform walking, jogging and running are given in Table 11 from Annex.

The values of the *step length* parameter are the segment measurements defined by two successive heal touchdown of the ground (Figure1 (a)). For walking, the measurements of *step length* can be taken in a single frame

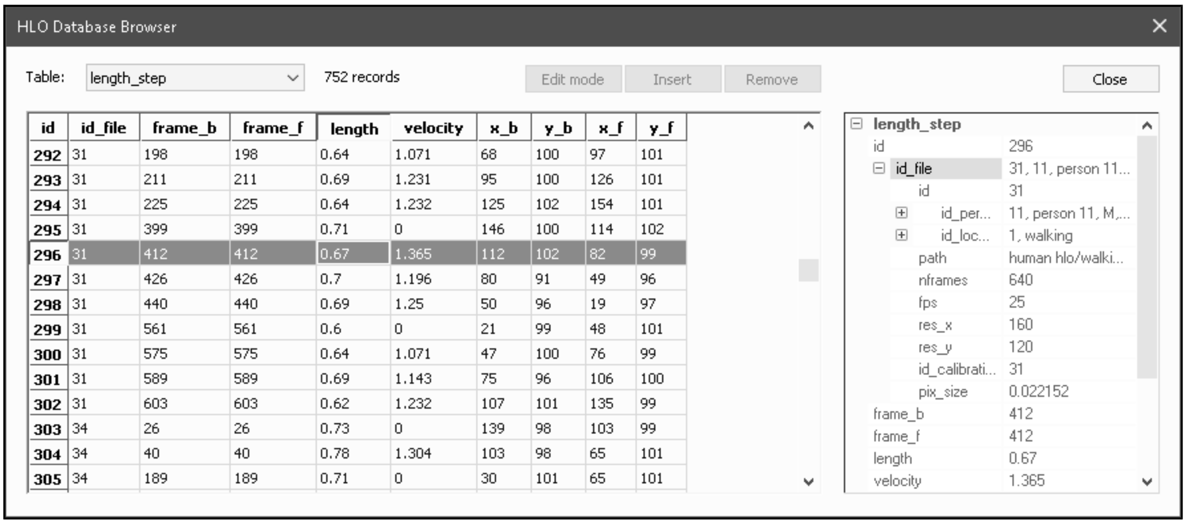


Figure 2. Interface for browsing HLO database (records from *step length* table)

when both feet are touching the ground. As it was mention before, in the running cycle for a period of time both feet are in the air. There for, the points that determines the *step length* for jogging and running are in different frames. This can be done only if the camera position is fixed, so the scene position doesn't change from one frame to another. The beginning and the end frames of the step (two successive heel touchdowns) and the frame rate determine the *frequency* parameter.

Because the video collection doesn't contain information about the height of the persons, it is assumed that men have the average height 1.75 m and women have the average height 1.65 m. In a calibration step, the pixel size which is required for lengths determinations is computed using person's height.

Having the *step length* parameter and *frequency* parameter, the *velocity* parameter is automatically computed in meter per seconds.

The measured angle parameters are: *bent angle*, *left ankle angle*, *left knee angle*, *right ankle angle*, *right knee angle*, and *between legs angle*. The position of the hand and the angle parameters of the hand were not taken into consideration in this study.

To describe and characterize human actions from images and video sequences using knowledge representation is necessary to define the main concepts related to movements. The main concepts defined in Human Locomotion Ontology (HLO) [12] are related with concepts about:

- joints and parts of the human body;
- frontal, sagittal, and transversal reference planes;
- upper, lower, left, right, front and back relative position defined by the reference planes;
- postural, frequential, and cinematic parameters described above;
- representation of the parameter with linguistic terms, such as low, medium, high or numerical values;
- human actions in this study are walking, jogging and running;
- human condition, such as age or physical condition (normal, disabled).

A relational database was created [13] to store the parameters measurements and it contains also additional important information about the video collection, persons, calibration step, type of locomotion and statistic parameters (minimum, maximum, average and standard deviation) computed by the application.

In [13], average, standard deviation and normal distribution functions for *angles* parameters and *step length* were graphically presented. From [12], [13], the most significant parameters are identified and can be used in HLO ontology to define concepts and rules that model human locomotion. The most significant parameters are *bent angle*, *angle between legs*, the lowest values of the *knee angle*, *step length*, and *velocity*.

Because some concepts in the HLO ontology are vague, fuzzy datasets were used to annotate the imprecise concepts [13]. By interpreting and analyzing the statistic results, membership functions are defined for the fuzzy datasets. For example, the *bent angle* parameter uses triangular membership functions defined for walking, jogging and running μ_{wb}, μ_{jb} and μ_{rb} as described in (1), (2), (3).

$$\mu_{wb}(x)=\begin{cases} x/4 & \text{if } x\in[0,4] \\ 1-\dfrac{x-4}{7} & \text{if } x\in[4,11] \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$\mu_{jb}(x)=\begin{cases} x-3/8 & \text{if } x\in[3,11] \\ 1-\dfrac{x-11}{8} & \text{if } x\in[11,19] \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$\mu_{rb}(x)=\begin{cases} x/14 & \text{if } x\in[0,14] \\ 1-\dfrac{x-14}{13} & \text{if } x\in[14,27] \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Regarding the *knee angle* parameters, it was noticed that the lowest value is significant in defining the type of locomotion. Thus, the trapezoidal membership function is used to define the lowest *knee angle* datatype for walking (93, 93, 137, 137), jogging (84, 84, 107, 107) and running (48, 48, 102, 102).

In HLO fuzzy ontology, all the membership functions are defined. For example, the declaration of the trapezoidal membership function of the lowest *knee angle* for running in our ontology is:

```
Declaration(Datatype(:RunningLowestKneeAngle))
AnnotationAssertion(:fuzzyLabel
                      : RunningLowestKneeAngle
   "<fuzzyOwl2 fuzzyType=\"datatype\">
   <Datatype type=\"trapezoidal\" a=\"48\"
             b=\"48\" c=\"102\" d=\"102\" />
   </fuzzyOwl2>")
DatatypeDefinition(:
  RunningLowestKneeAngle
    DataIntersectionOf
       (DatatypeRestriction (xsd:double
          xsd:maxInclusive "180.0"^^xsd:double)
       DatatypeRestriction(xsd:double
          xsd:minInclusive "0.0"^^xsd:double)))
```

3. K-means Classification

For writing the rules that describe the types of locomotion, the K-means clusterization algorithm [2] was applied in the space of the extracted parameters. To find the most significant parameters, the K-means clustering was applied for all their combinations in the training step (Figure 3).

In the training step it was used collected data from the first ten subjects of KTH video collection. The test step uses data from the eleventh subject of KTH video collection (Table 11 from Annex).

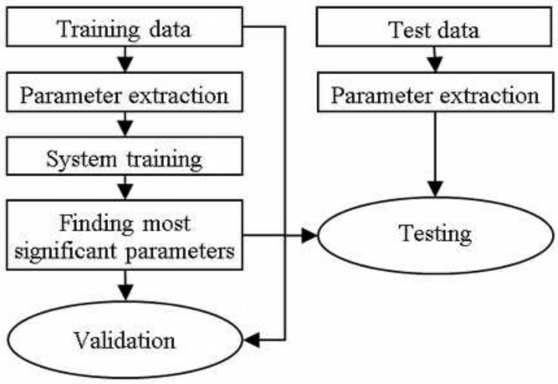


Figure 3. Classification model

Because the *velocity* parameter sometimes determines alone the locomotion type, two different situations were considered in clustering: with and without using the *velocity* parameter. To reduce the algorithm's complexity, from each item in the training dataset, only the minimum, maximum and average values of the parameters were considered.

The clustering results were evaluated using the purity measure [24]. Each cluster is assigned to the most frequent class to which the cluster's member belongs.

The purity is computed by evaluating the number of correctly assigned items using:

$$Purity=\frac{1}{n}\sum_{i=1}^{n} max\left|cluster_i \cap class_j\right|$$

where N is the number of training data vectors, $cluster_i$, i=1,N are the determined clusters and $class_j$, j=1,N are the known classes to which the data vectors belong.

The maximum value of purity measure is reached when all items are correctly classified and belong to the proper cluster.

4. Experimental Results

The following parameters were used in K-means clustering: maximum and average values of *bent angle* (β); minimum values of *left knee* *angle* (λ_l) and *right knee angle* (λ_r); average and maximum values of *between legs angle* (α); average and maximum values of *step length* (ρ); average value of *velocity* (v). A human action is represented by parameters vectors.

The Table 1 synthesizes the results of the clusterization for all parameters combinations and it was noticed that the best purity was reached in case of three and four parameter clusterization. The last column shows the number of combinations for which the best purity value was obtained.

Table 1. Synthesis of clusterization results

# Params	Best purity	# Best purity
1	0.967	1
2	0.967	6
3	1	1
4	1	1
5	0.967	16
6	0.967	6
7	0.967	1
8	0.9	2
9	0.833	1

The maximum value of purity measure obtained when clustering was performed for all parameters combinations is showed in Figure 4.

In case of two parameters clusterization there are six different solutions having the same

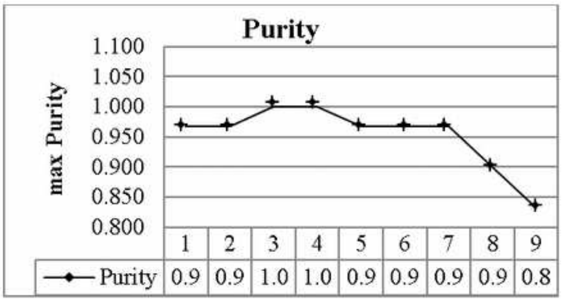


Figure 4. Synthesis of clusterization results.

purity = 0.967, which means that only one item was wrongly classified.

An example is presented below for the average *bent angle* and average *velocity* parameters. In clusterization walking is encoded as class 0, jogging is class 1 and running is class 2. The resulted coordinates of centroids for each class in case of two parameter clusterization are presented in Table 2.

Table 2. Coordinates of centroids (two parameters)

#	Class	β **AVG**	v **AVG**
0	0	3.230	1.460
1	2	13.744	3.794
2	1	7.300	2.357

In Figure 5, the three symbols indicate the original class of the parameters pair. The filled symbols indicate the position of centroids for each class. The only incorrectly classified item is marked by a circle in Figure 5.

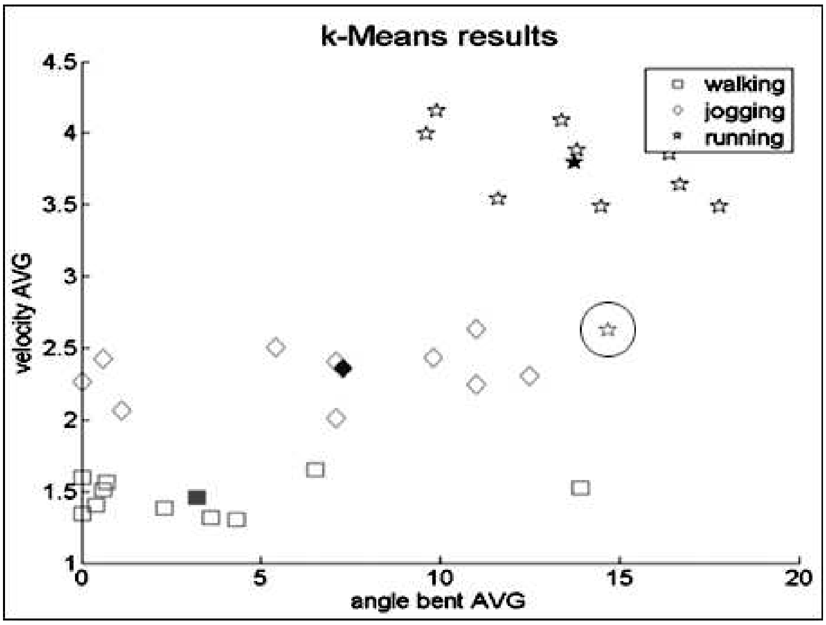


Figure 5. Two parameters - clustering results.

In Table 3 the validation results for two parameters clusterization are presented. The embossed row is the only item wrongly classified.

Table 3. Validation results in case of two parameters clustering

ID pers.	Class	#	*β* AVG	*v* AVG
0	0	0	4.3	1.301
0	1	2	7.1	2.404
0	2	1	11.6	3.542
1	0	0	13.9	1.527
1	1	2	12.5	2.303
1	**2**	**2**	**14.7**	**2.624**
2	0	0	3.6	1.317
2	1	2	11	2.636
2	2	1	13.8	3.882
3	0	0	0.4	1.402
3	1	2	0	2.263
3	2	1	16.7	3.645
4	0	0	2.3	1.384
4	1	2	9.8	2.432
4	2	1	14.5	3.486
5	0	0	6.5	1.649
5	1	2	11	2.248
5	2	1	16.4	3.858
6	0	0	0.7	1.566
6	1	2	5.4	2.507
6	2	1	13.4	4.091
7	0	0	0.6	1.512
7	1	2	7.1	2.014
7	2	1	17.8	3.491
8	0	0	0	1.598
8	1	2	0.6	2.428
8	2	1	9.6	3.995
9	0	0	0	1.346
9	1	2	1.1	2.063
9	2	1	9.9	4.153

The Euclidean distances between the parameters vectors extracted (average *bent angle*, average *velocity*) for the eleventh person from the test step (Figure 3) and the resulted centroids from Table 2 were computed and the resulted distances are in Table 4. Notice that for this case the eleventh person is classified correctly.

Table 4. Euclidean distances (two parameters)

	walking	jogging	running
Cluster **#0**	**1.243**	5.733	24.352
Cluster **#1**	12.013	5.102	**13.688**
Cluster **#2**	5.411	**1.642**	20.211

For three parameters clusterization, the maximum value of purity measure was obtained for the following combination of parameters: average *bent angle*, minimum *left knee angle* and average *velocity*. The results are depicted in Table 5 and Figure 6.

Table 5. Coordinates of centroids (three parameters)

#	Class	*β* AVG	λ_l MIN	*v* AVG
0	2	13.84	79.4	3.677
1	1	6.56	95.5	2.330
2	0	3.23	106.1	1.460

The Table 6 contains the results of the clusterization in case of three parameters. All items are correctly classified.

Also for this case, the Euclidean distances between parameters vectors average *bent angle*, minimum *left knee angle*, average *velocity* for the eleventh person from the test step (Figure

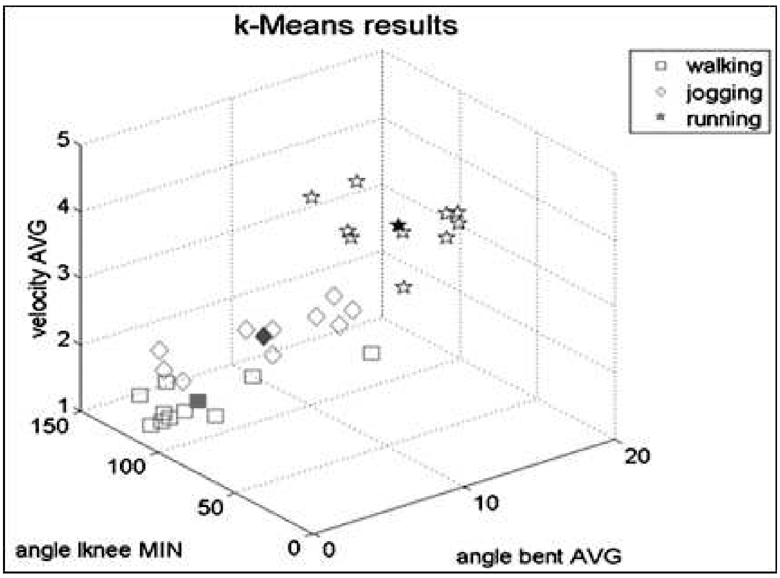


Figure 6. Three parameters - clustering results.

3) and the centroids (Table 5) were computed. The obtained results are given in Table 7. Notice that the eleventh person is classified correctly for all classes.

Table 6. Validation results in case of three parameters clustering

ID pers.	Class	#	*β* AVG	λ_l MIN	*v* AVG
0	0	2	4.3	137	1.301
0	1	1	7.1	95	2.404
0	2	0	11.6	88	3.542
1	0	2	3.9	98	1.527
1	1	1	2.5	96	2.303
1	2	0	4.7	84	2.624
2	0	2	3.6	98	1.317
2	1	1	1	94	2.636
2	2	0	3.8	48	3.882
3	0	2	0.4	102	1.402
3	1	1	0	84	2.263
3	2	0	6.7	68	3.645
4	0	2	2.3	105	1.384
4	1	1	9.8	93	2.432
4	2	0	14.5	83	3.486
5	0	2	6.5	102	1.649
5	1	1	1	90	2.248
5	2	0	6.4	66	3.858
6	0	2	0.7	119	1.566
6	1	1	5.4	96	2.507
6	2	0	3.4	102	4.091
7	0	2	0.6	102	1.512
7	1	1	7.1	95	2.014
7	2	0	7.8	87	3.491
8	0	2	0	93	1.598
8	1	1	0.6	105	2.428
8	2	0	9.6	71	3.995
9	0	2	0	105	1.346
9	1	1	1.1	107	2.063
9	2	0	9.9	97	4.153

Table 7. Euclidean distances (three parameters)

	walking	jogging	running
Cluster #**0**	25.214	19.176	**15.436**
Cluster #**1**	7.635	**3.355**	31.416
Cluster #**2**	**4.736**	10.03	41.829

In case of clusterization in the four parameters values space, the maximum value of purity was 1 for the following combination of parameters: maximum *bent angle*, average *bent angle*, average *between legs angle* and average *velocity* (Table 8), also obtained for three parameters. The classification was correctly for this case after applying Euclidean distances Table 9).

Table 8. Coordinates of centroids (four parameters)

#	Class	*β* MAX	*β* AVG	*α* AVG	*v* AVG
0	2	23.1	13.84	49.05	3.677
1	1	10.5	6.56	29.23	2.33
2	0	5.5	3.23	32.94	1.46

Table 9. Euclidean distances (four parameters)

	walking	jogging	running
Cluster #**0**	47.408	49.462	**24.917**
Cluster #**1**	11.848	**3.526**	43.754
Cluster #**2**	**5.306**	8.551	45.751

As it was specified, in all cases the best clusterization results were obtained when the *velocity* was included in the parameters list. We tested the clusterization without considering the *velocity* parameter. The best value obtained for purity measure was 0.90 for all parameters combinations, which means that three items were classified in a wrong class.

5. Discussions and Conclusions

This paper proposes a method to classify walking, jogging and running human actions based on the K-means algorithm. The purpose is to build a system model to recognize different human actions from video sequences using the parameters described in human locomotion ontology. The HLO ontology contains main concepts about human body parts, reference planes, relative position of a body part, parameters and their representation, human actions and conditions. Due the fact that some concepts are vague, fuzzy datasets were used to annotate imprecise concepts in the HLO ontology.

For this study KTH video collection was used which contains various types of locomotion, such as walking, jogging, and running. The extraction of parameters was semi-automatic, which means that the frames and the points that describe segments were manually selected and the values of the parameters were automatically determined. Typically, the sampling corresponds with the frames in which the segments are clearly defined.

As an objective criterion for the most significant parameters selection, the K-means algorithm was used. By evaluating the clustering results, two different combinations of three and respectively four parameters for which the purity measure reaches its maximum value on the training dataset were identified.

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Annex

Table 10. Statistics of the parameters for the first ten persons from KTH video collection

Human Locomotion	Parameter Name	#	Min	Max	Average	Standard Deviation
Walking	Bent Angle	100	0.00	18.00	3.23	4.41
	Left Ankle Angle	100	62.00	112.00	88.97	11.33
	Left Knee Angle	100	93.00	180.00	151.70	23.67
	Right Ankle Angle	100	60.00	151.00	87.97	13.73
	Right Knee Angle	100	84.00	180.00	148.26	25.50
	Between Legs Angle	100	0.00	60.00	32.94	15.72
	Step Length	352	0.59	0.92	0.72	0.06
	Velocity	249	0.91	1.86	1.29	0.17
Jogging	Bent Angle	100	0.00	19.00	6.56	5.01
	Left Ankle Angle	100	49.00	126.00	88.46	13.55
	Left Knee Angle	100	84.00	179.00	139.70	23.09
	Right Ankle Angle	100	45.00	129.00	83.75	13.71
	Right Knee Angle	100	75.00	178.00	137.13	25.04
	Between Legs Angle	100	1.00	60.00	29.23	13.44
	Step Length	259	0.58	1.16	0.89	0.11
	Velocity	259	1.52	2.98	2.24	0.28
Running	Bent Angle	100	0.00	39.00	13.84	6.14
	Left Ankle Angle	100	53.00	123.00	88.77	14.67
	Left Knee Angle	100	48.00	171.00	127.24	29.61
	Right Ankle Angle	100	53.00	120.00	86.32	13.95
	Right Knee Angle	100	54.00	177.00	132.34	29.02
	Between Legs Angle	100	0.00	89.00	49.05	19.99
	Step Length	141	0.80	1.83	1.29	0.20
	Velocity	141	2.14	7.10	3.74	0.81

Table 11. Statistics of the parameters for the eleventh person from KTH video collection used for testing

Human Locomotion	Parameter Name	#	Min	Max	Average	Standard Deviation
Walking	Bent Angle	10	0	3.81	2.013	0.983
	Left Ankle Angle	10	59.55	100.78	85.728	12.572
	Left Knee Angle	10	101.53	178.67	151.994	21.89
	Right Ankle Angle	10	63.43	95.39	81.983	9.939
	Right Knee Angle	10	118.19	174.49	154.886	17.405
	Between Legs Angle	10	25.66	48.75	37.814	6.605
	Step Length	17	0.6	0.71	0.665	0.034
	Velocity	13	1.071	1.365	1.206	0.089
Jogging	Bent Angle	10	6.12	11.69	8.925	1.604
	Left Ankle Angle	10	67.81	112.47	91.998	11.576
	Left Knee Angle	10	97.87	171.95	145.3	21.017
	Right Ankle Angle	10	73.83	102.99	91.684	8.18
	Right Knee Angle	10	90.17	166.76	133.131	26.281
	Between Legs Angle	10	20.84	47.74	31.549	8.872
	Step Length	16	0.69	0.89	0.808	0.049
	Velocity	16	1.725	2.472	2.119	0.191
Running	Bent Angle	10	21.04	32.47	27.425	3.651
	Left Ankle Angle	10	70.52	120.96	91.931	15.398
	Left Knee Angle	10	72.09	157.49	120.193	27.596
	Right Ankle Angle	10	71.57	102.82	84.329	9.827
	Right Knee Angle	10	47.27	152.38	112.234	34.747
	Between Legs Angle	10	30.46	88.35	60.739	16.348
	Step Length	6	1.17	1.6	1.407	0.142
	Velocity	6	4.056	4.444	4.217	0.118