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Recognition of Human Motion From Qualitative Normalised Templates

Chee Seng Chan · Honghai Liu · David J. Brown

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Abstract This paper proposes a Qualitative Normalised Templates (QNTs) framework for solving the human motion classification problem. In contrast to other human motion classification methods which usually include a human model, prior knowledge on human motion and a matching algorithm, we replace the matching algorithm (e.g. template matching) with the proposed QNTs. The human motion is modelled by the time-varying joint angles and link lengths of an articulated human model. The ability to manage the trade-offs between model complexity and computational cost plays a crucial role in the performance of human motion classification. The QNTs is developed to categorise complex human motion into sets of fuzzy qualitative angles and positions in quantity space. Classification of the human motion is done by comparing the QNTs to the parameters learned from numerical motion tracking. Experimental results have demonstrated the effectiveness of our proposed method when classifying simple human motions, e.g. running and walking.

Key words human motion classification · pattern recognition

1 Introduction

Human motion detection, coarse or fine body limb tracking and behaviour understanding of human action has attracted a great deal of interest in the last few

C. S. Chan (✉) · H. Liu · D. J. Brown
Institute of Industrial Research,
University of Portsmouth, Portsmouth PO1 3QL, UK
e-mail: cheeseng.chan@port.ac.uk

H. Liu
e-mail: honghai.liu@port.ac.uk

D. J. Brown
e-mail: david.j.brown@port.ac.uk

years. This interest is motivated by a wide spectrum of applications such as Human-Machine Interaction (HCI), security surveillance, medical diagnosis, sport analysis, the entertainment industry and, more recently, people recognition by gait analysis.

In this study, we concentrate solely on behaviour understanding. Behaviour understanding consists of the recognition and description of human actions and activities. The process of recognition is usually performed by comparing the observations to examples using techniques such as template matching, Hidden Markov Model (HMM) and dynamic Bayesian networks. However, accurate classification of human motion is still an under-constrained problem because the features usually used by previous methods reflect human body part motion and are generally provided by tracking algorithms. That is, the number of tracked points depends on the limbs involved in the actions i.e. the level of detail. Moreover, humans typically wear clothing which is loose or textured and, together with significant variations in the appearance of the human throughout the sequence, this makes the task even harder to identify limb boundaries and segment the main parts of the body. As a consequence, the more complex the human body model, the more accurate the tracking results but the more expensive the computation.

In this paper, we propose a qualitative reasoning approach to describe human motion in a video sequence. The proposed method employs fuzzy trigonometry [1] and it involves the construction of a human model, a qualitative representation of the prior knowledge of human motion and the Qualitative Normalised Templates (QNTs) (see Fig. 1 for the framework). Our starting point is a collection of the trajectories of the joint positions and/or joint angles of an articulated body. We assume availability of motion data that might be obtained by various methods; for example, the 2-D data used in our experiments was extracted from images using an algorithm similar to that of Isard and Blake [2]. The conventional robotic model is then employed to build up a generic vision model of a human model, that is to say, we employed the robotic kinematics to construct a stick model. The qualitative robotic model in [3] is adapted to construct the QNTs and, finally, human motion is classified by comparing the QNTs to the parameters learned using numerical motion tracking.

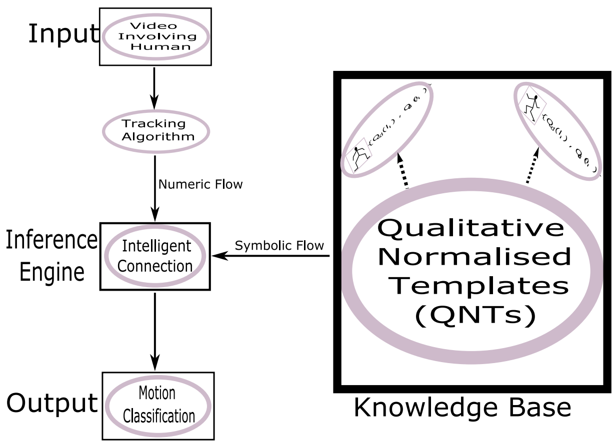


Fig. 1 Our proposed framework for human motion classification

What we do not present in this paper is the intelligent connection between numerical and symbolic data for human motion classification because this research is progressing and therefore will be presented separately. However, the preliminary experimental results have demonstrated the effectiveness of our proposed method when classifying simple human motions, e.g. running and walking.

This paper is structured as follows. We begin with a review of relevant prior art in Section 2. Section 3 introduces the QNTs, and describes in particular how we implemented the QNTs for human motion classification. Section 4 illustrates the conventional kinematic model that has been employed in robotics community, followed by our adaptation of the method into modelling human motion. Section 5 evaluates the proposed method and finally, concluding remarks are drawn.

2 Related Work

Human motion analysis is an interesting area to explore due to its highly complex, articulated motion. The ability to recognise humans and their activities is key for a machine to interact intelligently and effortlessly within social environments where visual analysis of human motion comes alive. Since then, many approaches such as HCI and visual surveillance have been adopted to analyse and recognise human behaviour where methods such as spatial and temporal characteristics have been considered. In the former, estimation of human body posture and localisation of body parts is used for analysis while the latter analyses specific features over time.

The simplest solution to the human motion classification problem is to build a wide range of motion databases and attempt to match the human pose extracted from an image sequence to the databases. For example in Haritaoglu et al. [4] and Wren et al. [5], the head and hand of a human are initially detected and then followed by tracking and fitting the features into a priori human model. In both studies, the 2-D features derived from the images are selected for motion recognition and have claimed early success. However, the motion is always constrained to simple movement such as walking in parallel to the image plane. Even though this solution is the easiest, it will inevitably suffer when more unconstrained and complex human movements are performed. As a result, HMM have been introduced for motion recognition and classification tasks. For example, parametric HMMs [6] have been employed for recognising gestures that exhibit dependence on a set of parameters.

Other research aims to reconstruct a human 3-D pose using multiple calibrated cameras and then compare the pose to predefined models. Conventionally, these approaches selected a few points from the reconstructed pose for motion classification. Then, these solutions have evolved into using 3-D joint coordination and, recently, 3-D joint angles as features for movement matching, as joint coordination was impractical due to the variations of human size.

In Fujiyoshi and Lipton [7], human motion was classified by determining the main posture using the inclination of the skeleton and exploiting temporal characteristics using cyclic motion analysis of its extremal points. In this approach, two motion cues, cyclic motion of a leg segment and posture of the torso segment were selected to analyse the motion of an individual target. The lower-left-most extrema point was selected as a leg segment while the upper-most extrema point was selected as the torso, then both vertical angles were calculated throughout the video sequence. The results showed that posture of walking and running can be easily distinguished by the angle of torso segment since the human torso tends to lean forward when running. Although such an approach is computationally inexpensive and does not require tracking specific features or a prior human model, it cannot be used by a system which has more sophisticated classification requirements.

In Ju et al. [8], the author proposed a method of view-based recognition of human activities as opposed to a method that analyses cyclic motion [7]. Instead, a temporal curve created by the estimated motion parameters was compared with a set of curves for known activities. The known curve (or characteristic curve) of each activity was obtained beforehand by automatically tracking the human model. Principal Component Analysis (PCA) was then employed to capture the dominant curve component and recognition of the activity was achieved by minimising the error. Unfortunately, this approach requires a sizable database to recognise human activity and it is only applicable to 2-D motion.

Lastly, but not least, other approaches include PCA [9], parameterisation of the motion of joint angles [10], snake fitting [11], mixed state statistical modelling [12, 13], Bayesian networks [14], local representation of motion based on optical flow [15, 16] and particle filters [17] for motion estimation and recognition.

3 Qualitative Normalised Templates for Human Motion

Fundamentally, the models which describe the geometric structure of the human body are stick figure, 2-D contour, volumetric models and hierarchical models. In this paper, we propose using a qualitative method to represent the human body: the qualitative normalised stick figure. This model uses fuzzy trigonometry [3] and it will be used as prior knowledge to predict motion parameters, and to interpret and recognise human behaviours. In addition, we also define a set of fuzzy qualitative states in quantity space known as the Qualitative Normalised Templates (QNTs) as human motion representation.

$$QNTs = \left[\, QS_a(\theta_i) \;\; QS_d(l_j) \,\right]^T \tag{1}$$

where $i = number\ of\ joints$ and $j = number\ of\ links$

This method has been proposed because recent research has showed that accurate tracking and localisation of the human body is still difficult. Theoretically, joint angles are sufficient for human motion recognition when we consider human motion as a series of movements of time-varying joint angles and link lengths. However, accurate recovery of these joint angles from a video is still not a well-solved problem. Moreover, the computational cost of model-based approaches is relatively high. Thus the proposed method, the qualitative normalised stick model, aims to negotiate the trade-offs between tracking precision and computational cost.

3.1 Qualitative Position Representation of Planar Robots

The proposed human model, the qualitative normalised stick figure, was inspired by the qualitative model of kinematic robots proposed by Liu et al. [3]. In the paper

[3], an n-link serial robot is described as a combination of links and joints which can be decomposed into n link-based segments, each of which consists of a link and its corresponding joint. Each segment is represented by a qualitative length and a qualitative orientation angle in quantity space. A qualitative representation of the robot's end effector is achieved by adding together the qualitative information of each link segment. For instance, with respect to the n-link robot, the direct kinematic of the planar robot can be described with the following equations:

$$\begin{aligned} x &= p(\theta) \\ \dot{x} &= J(\theta)\,\dot{\theta} \\ \ddot{x} &= J(\theta)\,\ddot{\theta} + \dot{J}(\theta,\dot{\theta})\,\dot{\theta} \end{aligned} \tag{2}$$

where

$$p(\theta) = \begin{bmatrix} p_x(\theta) \\ p_y(\theta) \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} l_i \cos\theta_i \\ \sum_{i=1}^{n} l_i \sin\theta_i \end{bmatrix}$$

where p is an n-dimensional vector function representing the direct kinematics. Unlike quantitative methods, the description of the ith link segment in qualitative reasoning requires the qualitative position parameters qp^i, qualitative length of the ith link qp_l^i and qualitative angle qp_l^θ. These are given in terms of constraint information:

$$\begin{cases} qp_l^i | qp_l^i \in \left[0\ l_i\right] \\ qp_\theta^i | qp_\theta^i \in \left[0\ 2\pi\right] \end{cases} \tag{3}$$

The intervals of the length and orientation angle of the ith link segment are described by the length parameter r_i and the orientation parameter s_i. The values of these two parameters are application dependent and subject to the system requirements.

$$\begin{cases} qp_l^i | qp_l^i \in \left[0, l_{i1}, l_{i2}, \ldots, l_{i(r_i-1)}, l_{ir_i}\right] \\ qp_\theta^i | qp_\theta^i \in \left[0, q\theta_{i1}, q\theta_{i2}, \ldots, q\theta_{i(s_i-1)}, 2\pi\right] \end{cases} \tag{4}$$

where

$$0 < l_{i1} < l_{i2} < \ldots < l_{i(r_i-1)} < l_{ir_i}$$

$$0 < q\theta_{i1} < q\theta_{i2} < \ldots < q\theta_{i(s_i-1)} < 2\pi$$

3.2 Qualitative Position of Unit Circle Representation

In [3], Liu et al. proposed a normalised unit circle (UC) as a qualitative representation of a robot's position such that the position of an end-effector undergoing continuous motion is normalised in the UC. The reason for this is to allow normalised symbols to be shared across multiple robots or subsystems. For example, the unit circle qualitative representation of the position of the end effector of the n-link planar robot can be derived as

$$\begin{cases} qp_l = \bigoplus_{i=1}^{n} qp_l^i \,|qp_l^i \in UC_{ql} \\ qp_\theta = \bigoplus_{i=1}^{n} qp_\theta^i \,|qp_\theta^i \in UC_{q\theta_i} \\ C_{dof} = UC_{dof} \end{cases} \tag{5}$$

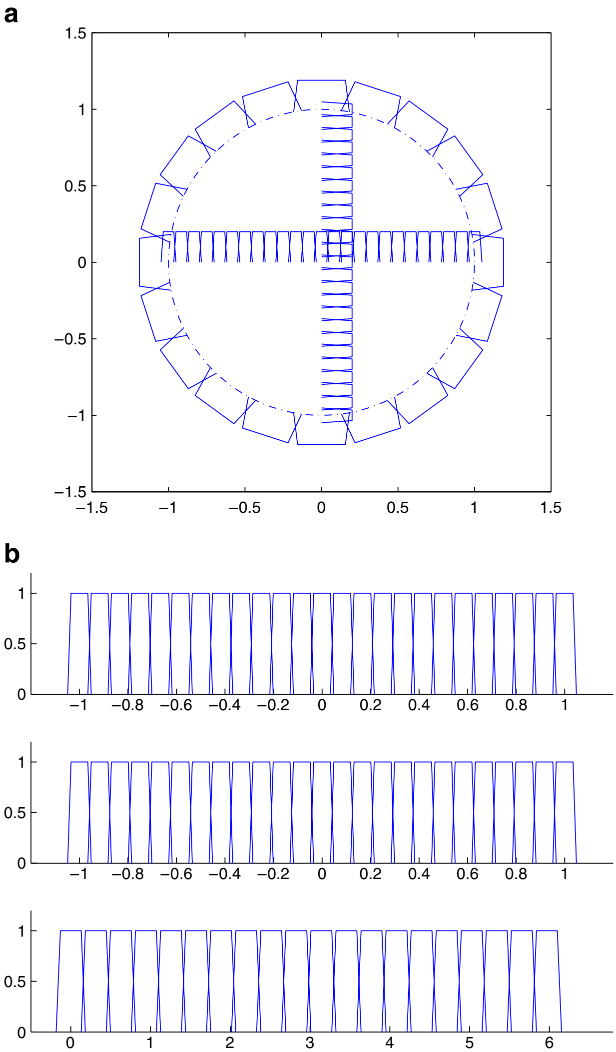
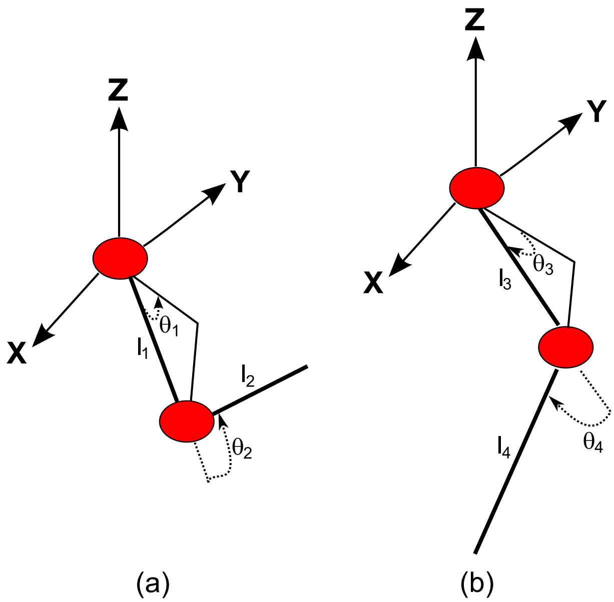


Fig. 2 **a** unit circle **b** fuzzy qualitative quantity space

Fig. 3 Human model: **a** arm model **b** leg model



where

$$UC_{qp_l} = \left[\frac{qp_1^i}{\sum_{i=1}^{n} l_i}, \frac{qp_2^i}{\sum_{i=1}^{n} l_i}, \cdots, \frac{qp_{(s_i-1)}^i}{\sum_{i=1}^{n} l_i}, \frac{l_i}{\sum_{i=1}^{n} l_i} \right]$$

$$UC_{qp_\theta^i} = \left[\frac{q\theta_1^i}{2\pi}, \frac{q\theta_2^i}{2\pi}, \cdots, \frac{q\theta_{(r_i-1)}^i}{2\pi}, 1 \right]$$

$$UC_{dof} = [qp_\theta^i = i], \; i \in (0, \; 1, \cdots, \; n)$$

where $UC_{qp_l^i}$ is the qualitative length of the ith link segment of the unit circle, $UC_{qp_\theta^i}$ is the qualitative orientation angle of the unit circle and $qp_\theta^0 = 0$ represents the base of the robot when i is equal to zero. The constraint function C_{dof} is used to define the degrees of freedom constraint between components.

The qualitative representation of a linear robot's end effector can be calculated by a qualitative addition of the translation and orientation components of each link segment based on its constrained degrees of freedom. The method used for the qualitative addition can be one of a variety of qualitative techniques. In particular, fuzzy arithmetic can be employed if the given components are described by fuzzy numbers. For our research, Fuzzy Qualitative Trigonometry (FQT) [1] is employed

Table 1 D-H structure for a simplified human arm

i	α_{i-1}	a_{i-1}	d_i	θ_i
1	0	0	l_1	θ_1
2	0	0	l_2	θ_2

Table 2 D-H structure for a simplified human leg

i	α_{i-1}	a_{i-1}	d_i	θ_i
3	0	0	l_3	θ_3
4	0	0	l_4	θ_4

for qualitative calculations and we introduce a fuzzy qualitative quantity space Q_X to represent the qualitative states of a Cartesian translation Q_X^d and orientation Q_X^a (see Fig. 2). This means that distance and angle measurements in fuzzy qualitative coordinates are dependent on the numbers and fuzzy characteristics of the elements of the fuzzy qualitative quantity space Q_X. As an example, the fuzzy qualitative version of a Cartesian position with an orientation range [0 Θ] and a translation range [0 L] can be described as

$$Q_X = \left\{Q_X^a, Q_X^d\right\} \tag{6}$$

where

$$Q_X^a = [QS_a(\theta_1), ..., QS_a(\theta_i), ...QS_a(\theta_m)]$$

$$Q_X^d = [QS_d(l_1), ..., QS_d(l_i), ...QS_d(l_n)]$$

where $QS_a(\theta_i)$ denotes the state of an angle, θ_i, $QS_d(l_j)$ denotes the state of a distance l_j and m and n are the number of elements of the two quantity spaces. It is noted that θ_1, l_1, θ_m and l_n are made equal to 0, Θ, L, respectively, to ensure that the description is closed.

3.3 Qualitative Normalised Human Model

In this paper, we adapt the qualitative model of kinematic robots described in the above subsection to a stick figure. We consider a simplified model of the human body where the arm and leg are each modelled as a two-link planar robot [18]. The links from the shoulder to the hand are labelled l_1 and l_2 and their joint angles are θ_1 and θ_2. The thigh to leg links are l_3, l_4 and their joint angles are θ_3 and θ_4 (see Fig. 3). Eq. 5 is selected to map these parameters to a normalised state and FQT [1] has been employed to perform the calculations involving these parameters. We normalise the

(a) (b)

Fig. 4 Tracking result: **a** walking **b** running

Table 3 Selected D-H parameters for human hand when walking

Frame	i	α_{i-1}	a_{i-1}	d_i(m)	θ_i(radian)
4	1	0	0	41	1.815
	2	0	0	38	0.540
8	1	0	0	40	1.768
	2	0	0	40	0.570
16	1	0	0	37	1.678
	2	0	0	44	0.235
32	1	0	0	36	1.432
	2	0	0	38	0.216

links qp_l^i and joint angles qp_θ^i in fuzzy qualitative terms to construct the stick model which allows us to negotiate the trade-offs between accuracy and computational cost by choosing the orientation and translation components of a fuzzy qualitative unit circle. The actual values of the links p^i and joint angles θ^i in their normalised terms are

$$p_l^i = \frac{l_i}{l}, \quad p_\theta^i = \frac{\theta_i}{2\pi} \tag{7}$$

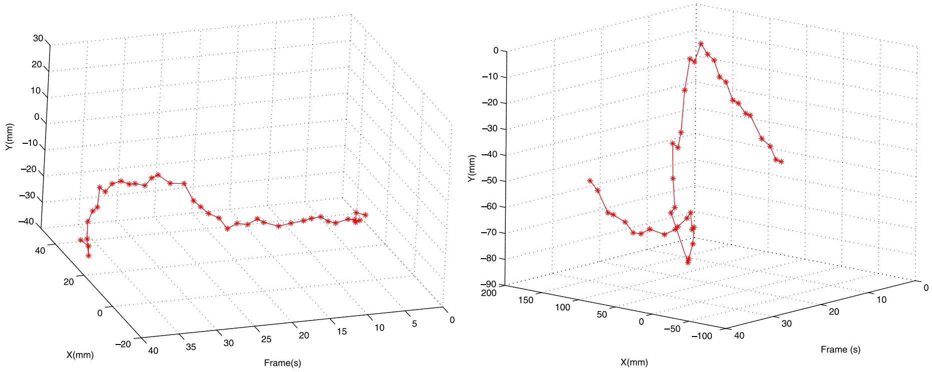
where $l = \sum_{i=1}^{2} l_i$ and i=1 and 2 or 3 and 4.

4 Human Motion Model

Kinematics is the study of movement without focus on the forces which affect the movement. The construction of a kinematic model for robot manipulators is a well-established field from a robotics perspective [19]. The unknown kinematic parameters are most commonly identified from the pose of the end effector or by measurement of the joint positions. Unfortunately, such information is not available when constructing a kinematic model of a human. However, this limitation does not constraint researchers from computer vision society because the identification of kinematic models for humans has been heavily studied since then, as well as in biomechanics society. Bregler and Malik [20] were the first to employ a kinematic model for motion estimation and this consideration motivated us to extend the framework to exploit a kinematic model as a representation of human motion. We

Table 4 Selected D-H parameters for human leg when walking

Frame	i	α_{i-1}	a_{i-1}	d_i(m)	θ_i(radian)
4	3	0	0	58	1.380
	4	0	0	52	0.021
8	3	0	0	45	1.206
	4	0	0	64	0.051
16	3	0	0	50	1.389
	4	0	0	70	0.673
32	3	0	0	48	1.826
	4	0	0	60	0.014



(a) (b)

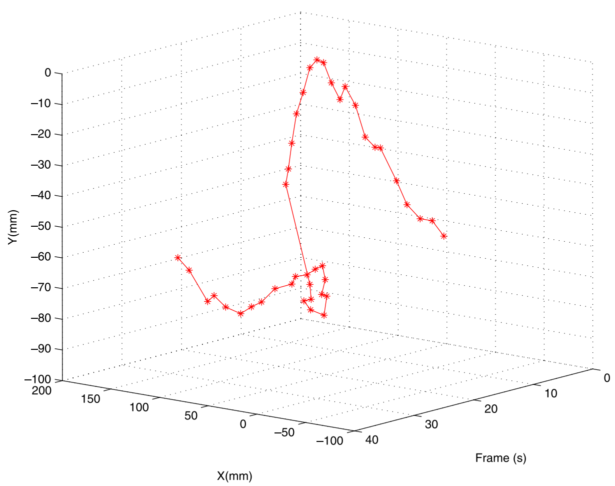
Fig. 5 Human model when walking: **a** arm **b** leg

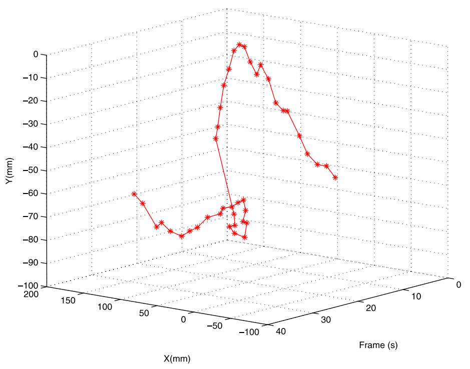
address the problem of finding a kinematic model of human motion in a video sequence. The ultimate goal is to build a system that, if properly initialised, can reliably model human motion from a sequence of images.

Let us denote an n-link spatial robot with a home position of $QS_d(\mathbf{p_0})$. The end-effector position $QS_d(\mathbf{p})$ can be obtained using the transformations of its link components $\mathbf{H}_i$ or the transformations ${}^{i-1}_{\ i}\mathbf{H}_{DH}$ in D-H parameter terms as follows:

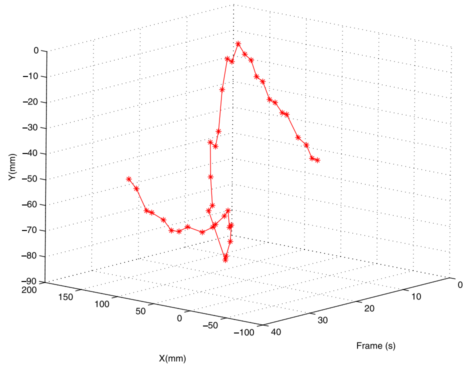
$$\mathbf{p} = \prod_{i=1}^{n} \mathbf{H}_i \cdot \mathbf{p_0} = \prod_{i=1}^{n} {}^{i-1}_{\ i}\mathbf{H}_{DH} \cdot \mathbf{p_0} \tag{8}$$

Fig. 6 Walking: this result shows the position of the knee with respect to the base frame of subject b





(a)



(b)

Fig. 7 Walking: **a** subject a **b** subject b. This result shows that both subjects have the similar walking pattern

where ${}^{i-1}_{i}\mathbf{H}_{DH}$ is a Denavit-Hartenberg (D-H) kinematic structure whose general form is given by

$$ {}^{i-1}_{i}\mathbf{H}_{DH} = \begin{bmatrix} C\theta_i & -S\theta_i & 0 & a_{i-1} \\ S\theta_i C\alpha_{i-1} & C\theta_i C\alpha_{i-1} & -S\alpha_{i-1} & -d_i S\alpha_{i-1} \\ S\theta_i S\alpha_{i-1} & C\theta_i C\alpha_{i-1} & C\alpha_{i-1} & d_i C\alpha_{i-1} \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{9} $$

where C stands for cosine; S stands for sine, θ_i is the rotation angle from X_{i-1} to X_i measured about Z_i, α_{i-1} is the twist angle from Z_{i-1} to Z_i measured about X_{i-1}, d_i is the distance from X_{i-1} to X_i measured along Z_i, the link offset a_{i-1} is the distance from Z_{i-1} to Z_i measured along X_{i-1}. X_i, Y_i, Z_i are the coordinate axes of the ith coordinate system for the ith link segment. For a graphical representation, please refer to Craig's book [19]. Furthermore, robot kinematics in Eq. 9 can be obtained as

$$ \mathbf{p}_e = \prod_{i=1}^{n} \mathbf{H}_{DH} \cdot \mathbf{p}_0 = \begin{bmatrix} \mathbf{R}_{3\times 3} & \mathbf{P}_{3\times 1} \\ 0_{1\times 3} & 1 \end{bmatrix} \cdot \mathbf{p}_0 \tag{10} $$

Table 5 Selected D-H parameters for human hand when running

Frame	i	α_{i-1}	a_{i-1}	d_i(m)	θ_i(radian)
4	1	0	0	41	1.595
	2	0	0	36	1.574
8	1	0	0	37	1.570
	2	0	0	29	2.000
16	1	0	0	41	0.888
	2	0	0	35	1.547
32	1	0	0	42	1.735
	2	0	0	29	1.899

Table 6 Selected D-H parameters for human leg when running

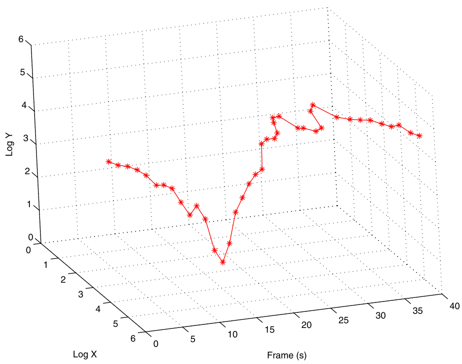
Frame	i	α_{i-1}	a_{i-1}	d_i(m)	θ_i(radian)
4	3	0	0	46	1.394
	4	0	0	60	0.257
8	3	0	0	45	1.256
	4	0	0	67	0.269
16	3	0	0	40	1.828
	4	0	0	65	1.467
32	3	0	0	57	1.232
	4	0	0	60	0.073

where $\mathbf{R}_{3\times3}$ represents the rotation about the axis and $\mathbf{P}_{3\times1}$ represents the translation along the axis. This is the de facto standard for modelling manipulators in the robotic industries [19].

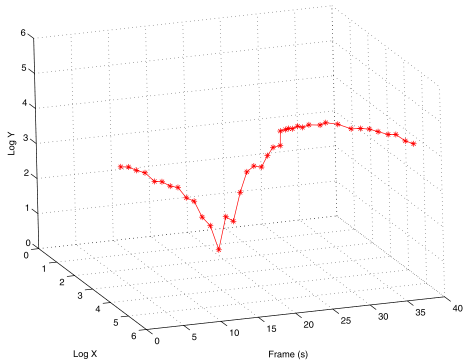
The kinematic model in Eq. 8 is employed to represent human motion in a planar direction. We model the human skeleton as a kinematic chain of rigid bodies. Each body segment is represented by a rigid link, and the links are connected together by joints. To restrict the set of admissible motions, we assumed that each joint allows a single degree of freedom: a rotation around its axis. This constraint is justified by the fact that the motion of the limbs can be approximated as planar around an axis perpendicular to the direction of motion [18]. The D-H structure of the human model is given in Table 1 and Table 2.

5 Experiments

In our first experiment, we tried to model and classify a planar human walking motion displayed in a sequence of frames by the proposed qualitative method. A sequence of 40 video frames of a human walking in parallel to the camera was collected (see Fig. 4). The frames were selected and the time domain of the signals was normalised to ensure that the start and end of the sequence were in phase



(a)



(b)

Fig. 8 Log scale walking: **a** subject a **b** subject b

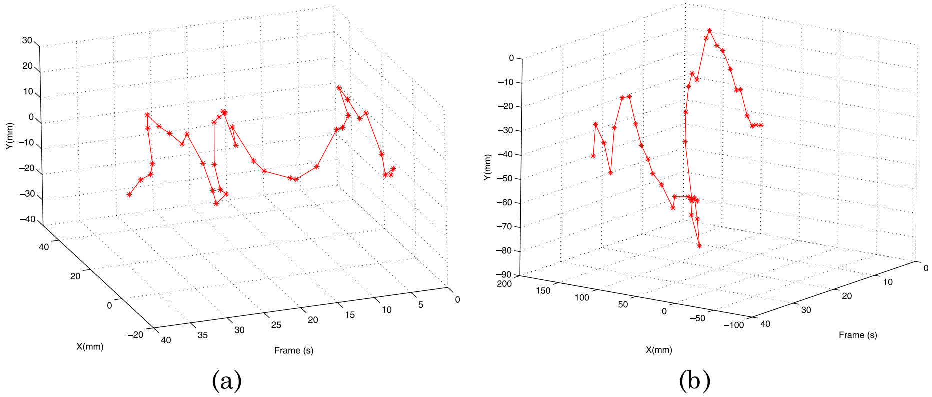


Fig. 9 Human model when running: **a** arm **b** leg

with the walking motion. This also ensured the inclusion of all phase angles when analysing the model and classification system. Each arm and leg was modelled as a two-link planar robot consisting of two links, l_i and l_{i+1}, and two joints, θ_i and θ_{i+1} (Fig. 3). The shoulder and the thigh position were selected as the base frame with the assumption that their relative position remained fixed throughout the video sequence. This reasonable assumption is supported by biomechanical research that concluded that when humans walk or run, the shoulder and hip positions are usually constant [21]. The kinematic model used was

$$P(\Theta) = \begin{bmatrix} p_x(\theta_1, \theta_2) \\ p_y((\theta_1, \theta_2) \end{bmatrix} = \begin{bmatrix} \sum_{k=1}^{2} (l_k \cos(\sum_{i=1}^{k} \theta_i) \\ \sum_{k=1}^{2} (l_k \sin(\sum_{i=1}^{k} \theta_i) \end{bmatrix}$$

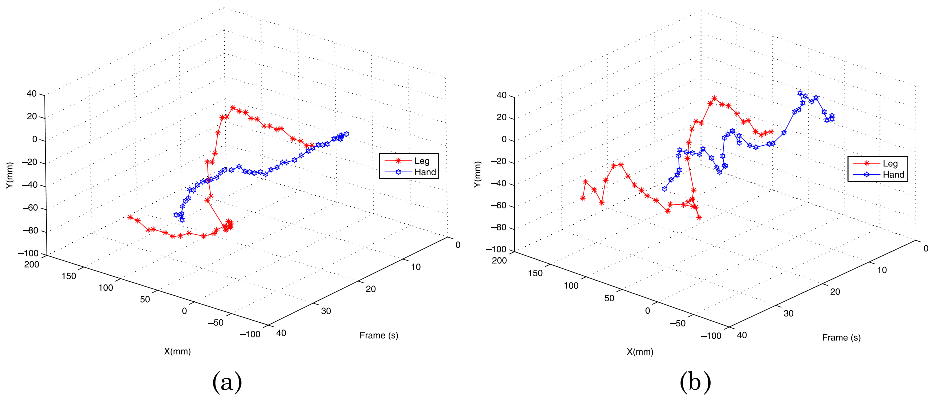


Fig. 10 Comparison: **a** walking **b** running. This result shows that both motion have different pattern

where l_1 and l_2 are link lengths and θ_1 and θ_2 are orientation angles. Equation 5 has been selected to map these parameters to a normalised state and fuzzy trigonometry was employed to calculate these parameters. We normalised the links qp_l^i and the joint angles qp_θ^i in fuzzy qualitative terms to construct a stick figure of the arm and leg. The D-H structure of the arm and leg motion are illustrated in Table 3 and Table 4. Based on the D-H parameters, the position of the hand and knee with respect to the base frame are shown in Fig. 5. The trade-offs between model accuracy and computational cost were negotiated by setting the orientation s_i and translation r_i components of a fuzzy qualitative unit circle.

We then tested our proposed method on a different subject who performed the same motion as in the first experiment. All the configurations and settings of the camera remained the same and the subject was required to walk in parallel to the camera as in the first experiment. Using the D-H parameters, we calculated the position of the knee with respect to the base frame and the results are shown in Fig. 6. Note that although the two different subjects performed the same motion, our proposed method still was able to capture the significant features of the periodic motion. The outcome demonstrates the efficiency and accuracy of the method since it is clear from Figs. 7 and 8 that a similar pattern has been achieved from walking, even though two different subjects were used.

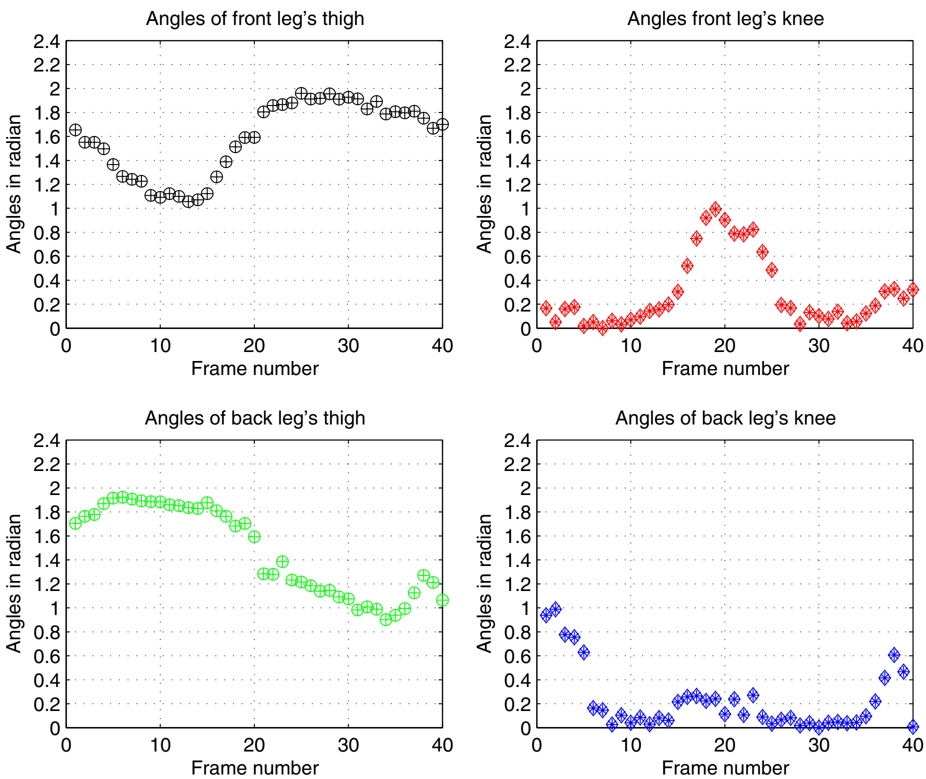


Fig. 11 Walking: human leg motion over a time period

In our next experiment, we employed the proposed approach to model a human running in parallel to the camera. As before, all the configurations and settings of the camera are the same as previous experiments but the subject performed a running motion in parallel with the camera. The D-H structure of the arm and the leg motion are illustrated in Table 5 and Table 6. Based on the D-H parameters, we calculated the position of the hand and leg using Eq. 8 (see Fig. 9).

These preliminary results have demonstrated the effectiveness of our proposed qualitative method for describing human motion in video sequences (see Fig. 10 for a comparison). The method uses fuzzy trigonometry and each human motion pose can be defined by a Qualitative Normalised Templates (QNTs).

6 Discussion

An understanding of the underlying mechanisms of a motion is essential to developing a model that is well suited to describe that motion. Naturally, human locomotion is rhythmic and produces a co-ordinated, oscillatory behaviour. One of the distinctive characteristics of walking and running is bilateral symmetry; that is, when one walks or runs, the motions of left and right leg are coupled by half-period phase shift.

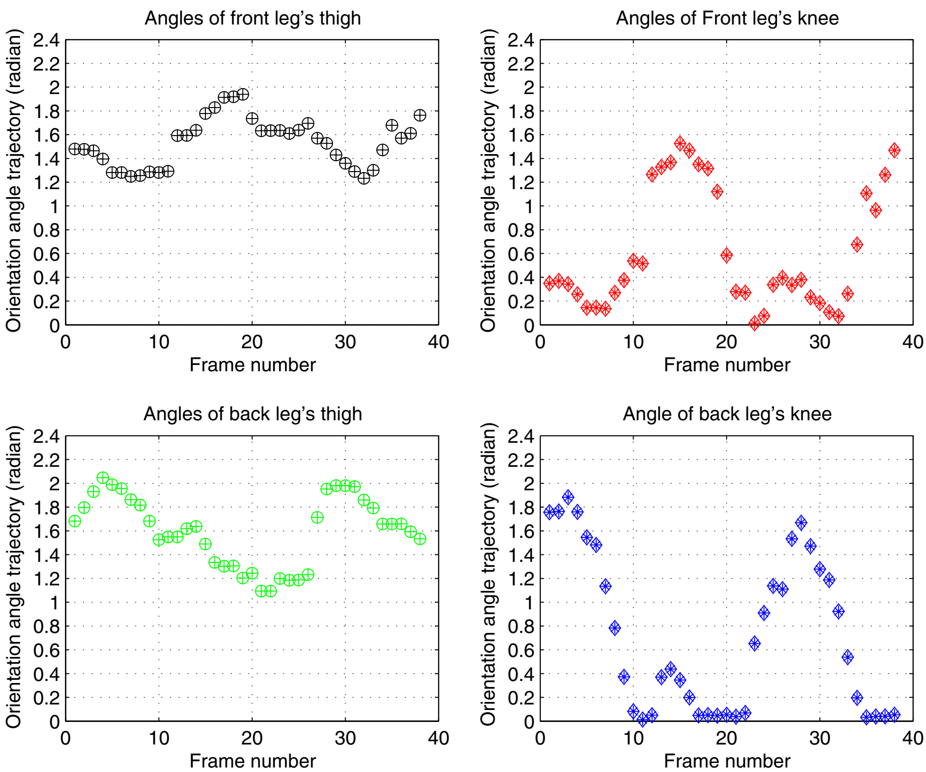


Fig. 12 Running: human leg motion over a time period

In terms of biomechanical definition, walking and running are distinguished firstly by stride duration, stride length, the velocities and the range of motion made by the limbs. That is to say, the kinematics of running differs from walking because the joint motions increase significantly as the velocity increases. This observation is supported by the medical community because running involves increased muscle activities and forces [21]. Another important difference between the kinematics of walking and running is whether there exist periods of double support and double float [22]. For walking, there will exist a period where both feet are in contact with the ground (double support) whereas for running, there will exist a period where both feet are not in contact with the ground (double float).

In our experiments, we have successfully identified these features when employing the proposed qualitative method to describe human motion (see Figs. 11 and 12). This has proved that our proposed method is consistent with biomechanical definitions and the precision of this method of modelling and classifying different human motions.

7 Concluding Remarks

In this paper, we present a qualitative framework for human motion classification. The proposed method uses fuzzy trigonometry and, in contrast to previous classification systems, we develop the Qualitative Normalised Templates (QNTs) to replace the matching algorithm (e.g. template matching) in video sequences. First, the conventional robotic model is employed to build up a generic vision model for a human model. Second, we adapt the qualitative robotic model to construct QNTs and, finally, classification of human motion is done by comparing the QNTs to the parameters learned from numerical motion tracking. This method has been inspired by using Fuzzy Qualitative Trigonometry (FQT) to manage the trade-offs between tracking precision and computational cost. The presented experimental results demonstrate the efficacy of our approach in terms of classifying simple human motion (e.g. walking and running). Our future work will aim to extend the proposed method to a fully-connected human body model. Furthermore, we anticipate that similar ideas could be used for 3-D motion classification and humanoid robots.

References

1. Liu, H., Coghill, G.M.: Fuzzy qualitative trigonometry. In: Proceedings of the IEEE International Conference on Systems SMC'05, Man and Cybernetics vol. 2, pp. 1291–1296 (2005)
2. Isard, M., Blake, A.: Condensation: Conditional density propagation for visual tracking. Int. J. Comput. Vis. (IJCV) **29**(1), 5–28 (1998)
3. Liu, H., Coghill, G.M., Xu, H.Y.: Qualitative modelling of kinematic robots for fault diagnosis. Int. J. Prod. Res. **43**(11), 2277–2290 (2005)
4. Haritaoglu, I., Harwood, D., Davis, L.S.: W4s: a real-time system detecting and tracking people in 2 1/2d. In: Proceedings of the 5th European Conference on Computer Vision-Volume I ECCV '98, London, UK, pp. 877–892. Springer, Berlin Heidelberg New York (1998)
5. Wren, C., Azarbayejani, A., Darrell, T., Pentland, A.: Pfinder: real-time tracking of the human body. In: Proceedings of the 2nd International Conference on Automatic Face and Gesture Recognition FG'96, Washington, DC, p. 51. IEEE Computer Society (1996)
6. Wilson, A.D., Bobick, A.F.: Parametric hidden markov models for gesture recognition. IEEE Trans. Pattern Anal. Mach. Intell. (PAMI) **21**(9), 884–900 (1999)

7. Fujiyoshi, H., Lipton, A.J.: Real-time human motion analysis by image skeletonization. In: Proceedings of the 4th IEEE Workshop on Applications of Computer Vision WACV '98, Washington, DC, p. 15. IEEE Computer Society (1998)
8. Ju, S.X., Black, M.J., Yacoob, Y.: Cardboard people: a parameterized model of articulated image motion. In: Proceedings of the 2nd International Conference on Automatic Face and Gesture Recognition FG '96, Washington, DC, p. 38. IEEE Computer Society (1996)
9. Yacoob, Y., Black, M.J.: Parameterized modeling and recognition of activities. Comput. Vis. Image Underst. (CVIU) **73**(2), 232–247 (1999)
10. Campbell, L.W., Bobick, A.F.: Recognition of human body motion using phase space constraints. In: Proceedings of the Fifth International Conference on Computer Vision ICCV '95, Washington, DC, p. 624. IEEE Computer Society (1995)
11. Niyogi, S., Adelson, E.: Analyzing and recognition walking figures in xyt. In: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition CVPR '94, pp. 469–474 (1994)
12. Pavlovic, V., Rehg, J., MacCormick, J.: Impact of dynamic model learning on classification of human motions. In: Proceedings of the International Conference on Computer Vision and Pattern Recognition CVPR '00 (2000)
13. Bregler, C.: Learning and recognizing human dynamics in video sequences. In: Proceedings of the 1997 Conference on Computer Vision and Pattern Recognition CVPR '97, Washington, DC, p. 568. IEEE Computer Society (1997)
14. Madabhushi, A., Aggarwal, J.K.: A bayesian approach to human activity recognition. In: Proceedings of the Second IEEE Workshop on Visual Surveillance VS '99, Washington, DC, p. 25. IEEE Computer Society (1999)
15. Hoey, J., Little, J.J.: Representation and recognition of complex human motion. In: Proceedings of the Conference on Computer Vision and Pattern Recognition CVPR '00 (2000)
16. Little, J.J., Boyd, J.E.: Recognizing people by their gait: the shape of motion. J. Comput. Vis. Res. **1**(2), 1–33 (1998)
17. Black, M.J., Jepson, A.D.: A probabilistic framework for matching temporal trajectories: condensation-based recognition of gestures and expressions. In: Proceedings of the 5th European Conference on Computer Vision-Volume I ECCV '98, London, UK, pp. 909–924. Springer, Berlin Heidelberg New York (1998)
18. Chan, C.S., Liu, H., Brown, D.J.: Human arm-motion classification using qualitative normalised templates. In: Knowledge-Based Intelligent Information and Engineering Systems KES '06. LNAI, vol. 4251, pp. 639–646. Springer, Berlin Heidelberg New York (2006)
19. Craig, J.: Introduction to Robotics: Mechanics and Control. Addison-Wesley Reading, Boston, MA (1989)
20. Bregler, C., Malik, J.: Tracking people with twists and exponential maps. In: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition CVPR '98, Washington, DC, p. 8. IEEE Computer Society (1998)
21. Ounpuu, S.: The biomechanics of walking and running. Clin. Sports Med. **13**(4), 843–863 (1994)
22. Thordarson, D.: Running biomechanics. Clin. Sports Med. **16**(2), 239–247 (1997)