

# Wavelet Features in Motion Data Classification

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**Abstract.** The paper deals with the problem of motion data classification based on result of multiresolution analysis implemented in form of quaternion lifting scheme. Scheme processes directly on time series of rotations coded in form of unit quaternion signal. In the work new features derived from wavelet energy and entropy are proposed. To validate the approach gait database containing data of 30 different humans is used. The obtained results are satisfactory. The classification has over than 91% accuracy.

**Keywords:** motion capture, gait identification, multiresolution analysis, feature extraction, lifting scheme, wavelet energy, wavelet entropy, motion data classification

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## INTRODUCTION

Motion capture data give a digital representation of the complex temporal structure of human motion. The most precise measurements of motion are obtained by optical motion capture systems. The positions of the markers are tracked by set of calibrated cameras. The 3D coordinates of the markers are reconstructed on the basis of gathered data. Markers are appropriately mapped to the skeleton model. They are further transformed into a kinematic chain representation with hierarchical structure related to specified skeleton model. The root object is described by its global position and orientation. Child objects corresponding to connected bones are defined by rotations relative to their parents. The proposed method is based on unit quaternion signals for every joint in skeleton model which represent change of rigid-body orientation in time.

Paper describes the new feature extraction for the classification of motion capture sequences. This classification task is challenging due to the data being complex, high dimensional and time-variant [1, 2]. Motion data signals are decomposed into simpler representations in different scales using the second generation wavelet based multiresolution technique. As a result, motion descriptors derived from wavelet energy and entropy are formed. The final recognition is carried out by the nearest neighbor and naive Bayes classifiers. The introduced method is successfully validated with the usage of real data referring to the human gait identification challenge problem.

## WAVELET MULTIREOLUTION ANALYSIS BY QUATERNION LIFTING SCHEME

The main idea of multiresolution analysis is to represent a signal in the form of a coarse to fine hierarchy. The analyzed signal is decomposed into general data descriptions – the global pattern of the signal – and a hierarchy of its details (wavelet coefficients). Multiresolution methods for motion data are very often derived from classical digital signal processing techniques. Most solutions are based on processing orientation data as three uncorrelated signals defined by single Euler angle.

The lifting scheme is a second generation wavelet tool and allows construction and efficiency implementation wavelets transformation on non-standard structures of data while keeping all classical wavelets powerful properties, as speed and high ability of approximation [3, 4].

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We use Linear Quaternion Lifting Scheme (LQLS) [5] and Spline Quaternion Lifting Scheme (SQLS) [6] which are constructed directly on the quaternion signal in accordance to the principles of quaternion algebra allows simultaneous processing of correlated orientation data. The LQLS is based on spherical linear (SLERP) quaternion interpolation method. The SQLS uses SQUAD interpolation in tangent space. The SQLS scheme is based on tangent space so the detail coefficients are vector in  $R^3$ . For the unifying the representation the vectors are converted to quaternion by exponent mapping  $R^3 \rightarrow \mathbb{H}_1$ . The detail coefficients for every resolution are represented by vectors: 4-elements quaternion. If there is no difference we get a zero rotation identity quaternion  $q_0 = (1, 0, 0, 0)$ .

## CLASSIFICATION

### Gait Database

To validate the proposed feature extraction, a motion database is collected. It contains data from 436 gaits of 30 different males between the ages of 20-40 (the database was also used in [2]). The gait route is a straight line of about five meters long.

The default skeleton model of Vicon Blade with 22 segments is applied. Thus, pose configuration space is specified by 23 rotations – the additional one is related to global skeleton rotation. A three dimensional translation vector is not taken into consideration by feature extraction process, it is removed in preprocessing stage.

The classification considers only the main cycle containing two middle adjacent steps, which is representative for whole gait. To detect it, a tracking of extremes of distances between left and right feet is carried out. After linear normalization in the time domain of motion sequences, 128 ( $n = 2^7$ ) samples were extracted as representing detected main cycle.

### Features Extraction

Input motion signal with length  $n = 2^k$  is a set of unit quaternions. The upper index  $j$  indicates the scheme step (the level of resolution) where  $j + 1$  is a lower resolution level than  $j$ . The  $j + 1$  resolution signal is obtained by removing every second sample from the previous  $j$  resolution signal.

Let us assume that a signal consists of quaternions:  $Q = q_1, q_2, \dots, q_n$ , where  $q_i \in \mathbb{H}_1$  and  $n = 2^k$  for some  $k \in \mathbb{N}$ . Furthermore, the signal is processed by the selective negation (hemispherization), i.e. every quaternion  $q_i$  ( $i > 1$ ) is converted to  $-q_i$  if  $\langle q_i, q_{i-1} \rangle < 0$ , because of duality of unit quaternions representing rotations. It satisfies that two adjacent quaternions are located on the same hemisphere.

After applying lifting scheme (LQLS or SQLS) on original signal (the highest  $j = 1$  resolution) we get lower resolution  $j + 1$  approximation quaternion signal  $Q^{j+1} = q_1^{j+1}, q_2^{j+1}, \dots, q_{\frac{n}{2}}^{j+1}$  and quaternion detail signal  $D^{j+1} = d_1^{j+1}, d_2^{j+1}, \dots, d_{\frac{n}{2}}^{j+1}$ . In next step the lifting scheme is applied on an approximated signal. As a result we get multi-resolution representation of quaternion motion data signal.

We define features based on wavelet definition of energy at each resolution level  $j$  as follows:

$$E_{d,j} = \frac{\sum_i \|d_i^j\|^2}{n^j}$$

where  $n^j$  is the number of detail coefficients on  $j$  level. Because the rotations are coded as unit length quaternion, as a metric we use the geodesic distance to identity quaternion  $(1, 0, 0, 0)$ :

$$m_{geodesic}(q_1, q_2) = \begin{cases} \frac{1}{\pi} \arccos(\langle q_1, q_2 \rangle) & \text{if } \arccos(\langle q_1, q_2 \rangle) \leq \pi \\ 1 - \frac{1}{\pi} \arccos(\langle q_1, q_2 \rangle) & \text{otherwise} \end{cases}$$

In similar form the approximation coefficients energy at each level is defined:

$$E_{q,j} = \frac{\sum_i \|q_i^j\|^2}{n^j}$$

In consequence, the total energy can be obtained by:

$$E_T = E_{q,r} + \sum_{j=1}^r E_{d,j}$$

where  $r$  is the number of generated resolution levels

Then, the normalized values, represent the relative wavelet detail coefficients energy:

$$E_{R,j} = \frac{E_{d,j}}{\sum_j E_{d,j}}$$

The relative wavelet energy provides information about the relative energy associated with different frequency bands present in the signals and their corresponding degree of importance.

The wavelet entropy can provide useful information about the underlying dynamical process associated with the signal. It provides a measure of the information which gives a measure of the degree of similarity between two probability distributions. We propose relative entropy definition of multiresolution representation:

$$\rho = - \sum_j E_{R,j} \ln(E_{R,j})$$

Wavelet energy and entropy is used to extract the features from surface EMG and EEG signal [7, 8]. In such the case the classification is based on classic wavelet analysis implemented in form of filter bank. The using of energy and especially entropy features provides distinctive features about the signal and reduces the size of feature vector.

Reassuming, the proposed approach of motion data classification is based on the new wavelet energy and entropy like features computed from multiresolution representation. It is applied to all 23 joints of given skeleton model. For every level ( $j = 1 \dots 7$ ) the  $E_{d,j}$ ,  $E_{q,j}$ ,  $E_{R,j}$  are calculated. For whole multiresolution analysis we get  $\rho$  and  $E_T$ . In total there are 529 of number attributes. What it is significantly lower number compared to the features based on all quaternion wavelet coefficients.

## Classification

In the proper classification stage,  $k$  statistical nearest neighbors and Naive Bayes classifiers are applied [9]. To compute distances between obtained motion descriptors classical Euclidean and Manhattan metrics are chosen. The obtained scales of subsequent attributes are different, because of various range of movements of skeleton joints and considered wavelet features. Thus, in another variant normalization of input vector space is carried out. In estimation of feature space necessary in the training stage of Naive Bayes classifier, parametric and non-parametric approaches are taken into consideration.

## Results

The collected database is split into training and testing parts according to sessions. In the classification, data from different scales are taken into consideration. To recognize motion descriptors, nearest neighbors (kNN - 1NN, 3NN and 5NN) and naive Bayes (NB - with normal and kernel based estimation) classifiers are applied.

In Table 1 the best classification results of 1NN classifier are presented. Due to the nature of transform, classification results based on SQLS are better. In determining the wavelet coefficients SQLS takes four samples, not just two as LQLS. Individual energy values on every scale assigned to features are insufficient for classification. The best results were obtained using all measures (ALL in Table 1 means  $E_d$ ,  $E_T$ ,  $E_q$ ,  $E_R$  and  $\rho$ ). The strongest individual features, which give the most precise recognition, are reflected by scale 5 and 6. They contain important individual features which allows for efficient classification. This is also confirmed by improved results for classification based on the energy calculated on the basis of wavelet coefficients ( $E_d$  for level 5 and 6). More detailed scales 1-4, which focus on the local gait characteristics, are influenced by a greater acquisition noise and are ambiguous in respect to considered gait identification problem. This is a reason for noticeably worse performance of recognition for those scales. The 1NN classifier usually has the greatest precision and there is an opposite dependency between number of nearest neighbors and obtained recognition accuracy.

**TABLE 1.** The obtained accuracy of the classification by INN

	INN											
	$E_d$		$E_T$		$E_q$		$E_R$		$\rho$		ALL	
	LQLS	SQLS	LQLS	SQLS	LQLS	SQLS	LQLS	SQLS	LQLS	SQLS	LQLS	SQLS
LEVEL_1	47,75	47,75	62,92	63,48	60,67	60,67	48,88	45,51	57,87	51,69	84,27	87,64
LEVEL_2	40,45	48,88			60,67	60,67	51,12	47,75			85,96	84,27
LEVEL_3	43,26	32,02			60,67	61,24	48,31	51,69			86,52	88,20
LEVEL_4	59,55	67,98			60,11	60,11	51,69	47,75			86,52	87,64
LEVEL_5	72,47	56,18			61,24	63,48	57,87	57,30			87,08	<b>91,57</b>
LEVEL_6	76,97	72,47			60,67	65,73	61,24	59,55			89,33	<b>91,57</b>
LEVEL_7	76,97	69,66			60,67	62,36	64,61	62,36			87,64	88,20

## SUMMARY

One of the most often used classification approaches of motion data utilizes feature extraction and selection. In this case, and on the basis of multiresolution representation of quaternion time series data, a set of new attributes is determined, which forms a motion descriptor. Our main contribution is adaptation of wavelet energy and entropy to multiresolution representation of quaternion signal. As a validation such defined features were successfully applied to human gait identification challenge problem.

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Data was captured in Human Motion Laboratory in Bytom, Poland (<http://hm.pjwstk.edu.pl/en/>).

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