Probabilistic LMA-based Classification of Human Behaviour Understanding Using Power Spectrum Technique

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Abstract – *This paper proposes a new approach for the Power Spectrum (PS)-based feature extraction applied to probabilistic Laban Movement Analysis (LMA), for the sake of human behaviour understanding. A Bayesian network is presented to understand human action and behaviour based on 3D spatial data and using the LMA concept which is a known human movement descriptor. We have two steps for the classification process. The first step is estimating LMA parameters which are built to describe human motion situation by using some low level features. Then by having these parameters, it is possible to classify different human actions and behaviours. Here, a sample of using 3D acceleration data of six body parts to obtain some LMA parameters and understand some performed actions by human is shown. A new approach is applied to extract features from a signal data such as acceleration using the PS technique to achieve some of LMA parameters. A number of actions are defined, then a Bayesian network is used in learning and classification process. The experimental results prove that the proposed method is able to classify actions.*

Keywords: Human behaviour understanding, Laban movement analysis, power spectrum technique, action recognition, Bayesian network.

1 Introduction

Human behaviour modeling is one of the big challenges in artificial intelligence science. There are many applications related to the subject for example; surveillance systems (e.g. airport, bank, train station, etc.), virtual reality (e.g. interactive virtual worlds, virtual studios teleconferencing, etc.), motion analysis (e.g. choreography of dance, clinical studies of orthopedic patients, etc.) and Human-Robot Interaction (HRI).

Human behaviour comes from different human actions and reactions which usually appear by the persons body motion, voice and facial expressions. Researchers are investigating all the possibilities to recognize human behaviours depending on their applications [17].

Nowadays, most of the related applications (such as the surveillance systems) rely on the human movements. Bobick [5] presented a survey related to human movement, activity and action or behaviour. In Bobick's terminology, the movements are the lowest level of human motions which do not need any previous knowledge to be identified, but to understand human action or behaviour we need to recognize a sequence of human movements or states, related to the environment or scenario.

We present the example for fall detection case to better understand the importance of the studies in the area of human behaviour analysis. Falls are among the top causes of unintentional injury and death in the elder population. Several studies point out for the social impact of this problem, which reach global scale [24] [6]. Falls in older people are estimated to affect 30% of those over 65 in the annual basis approximately. Although most falls procure no injury, between 5-10% of elders who fall each year sustain serious injury, such as fracture, head trauma, or serious laceration. Of the estimated 1% of elders who fall and sustain a hip fracture, 20-30% die within one year of the fracture. As many as two thirds of elders with hip fracture never regain their pre-fracture activity status and one-third require nursing home placement. Consequently, the economical impact related with falls is expected to reach near $55 billion as the babys boomer age en masse, just for USA. World wide efforts are spent in order to work in the prevention of these situations either studying methodologies for prevention as [19] or designing fall detection systems [26] which try to help in nursing tasks.

Given these facts, human behaviour analysis can contribute with a strong point both on the prevention and detection of this type of hazardous situations. Systems monitorizing the elder living space could analyse for potential risks of falls occurring and identify potential causes for falling and consequently leading to correct adaptations on the living space. In terms of fall detection, it would be advantageous, for those situations where full monitoring is not possible, have still systems with the capabilities for alarming carers about abnormal situations.

One of the common approaches to obtain the input data for applying human behaviour analysis techniques is using motion trackers which are more precise than the other trackers. We use a special suit (MVN®) which has several IMUs attached to collect the interesting data such as position and acceleration of some body parts. We attempted to use some features which can be obtained by a multi-sensor framework instead of motion tracker such as [1, 2] that presented a multi-modal and multi-layer homography based framework.

One of the basic problem is to define some useful Low Level Features (LLF) and observable information which are depended on the environment and type of the input data. The interested features are depending on the type of data that we intend to achieve from a person. Most of the attempts rely on the human motions [18]. Image based and 3D based are known approaches to extract the features. Recently, researchers are interested to use 3D data as input to reconstruct any object such as human body in order to avoid limitations of image based approaches. Although it is usually more time consumer.

1.1 Previous work

Gong et al. in [10] presented an approach to describe human behaviours by using face and body properties. Their approach attempted to analyze spatial correlations among non-adjacent for estimating behaviour using both facial properties and body gestures. A mixture of Multi-Observation Hidden Markov Model (MOHMM) based approach was presented to learn specific behaviour classes for automatic detection of abnormalities on-the-fly to use in real-time anomaly detection and normal behaviour recognition. And then Xiang and Gong in [27] presented a MOHMM-based general activity detection method which applied on surveillance video data.

Arsic et al. in [4] discussed a real-time behaviour detection method which is based on video. Their application is for passenger behaviour detection in public transport such as airplane. They defined some special human behaviours such as aggressive, nervous, tired, kid and talk.

Hanging et al. in [11] illustrated an approach for complex multi-agent human activities (e.g. stealing). They supposed each human activity include some action threads by an actor. Thus they defined a Bayesian network which uses some LLFs (trajectory and shape of moving blob) to recognize the action threads.

Leo et al. in [13] showed an approach for complex human activities detection from image sequences in outdoor environment such as archaeological site (e.g. walking, probing the subsoil by a stick, damping the ground with a tank and picking-up some objects from the ground).

Nascimento et al. in [16] described a method for recognizing some human activities in a shopping space. They used human motion patterns which are achieved from a sequence of displacements of each human's blob center. They modeled trajectories of the Hyman's blob by using a method which they called *a multiple dynamical models with a switching mechanism*. Finally, they estimated the identification of the models which connected with a trajectory.

Ye et al. in [28] showed an image-based method which used human body part segmentation approach for covering weakness of the visual hull method for concave regions reconstruction. The first result was virtual silhouette image fit to the given viewing direction which used human body part localization method. Body parts produced separately in virtual view from the corresponding input views and then assembled together. Last silhouette image was used for removing the separate or squeezed region in final view.

Recently, researchers attempt to use advantages of human movement descriptors which include some useful knowledge about efficient parameters involving to human motions. Laban Movement analysis (LMA) is a known system, that there are some literature's like [29, 23, 15] which have attempted to formulate LMA parameters to interpret human motion by an intelligence system.

Rett & Dias in [21] presented a system that analyses human movements online, based on the concept of the LMA. They implemented a Bayesian model for learning and classification. They presented the Laban Movement Analysis as a concept to identify useful features of human movements to classify human gestures based on vision and motion tracker data. However they did not design their system to be able to classify human actions like walking. because they focused just on human gestures which just need hands and head positions.

Our aim is to detect human activity by estimating power characteristic of human body parts during different actions. As Rett in [22] presented a method to use LMA to detect human gestures, one of the special LMA components is *Effort* which *deals with the dynamic qualities of the movement and the inner attitude towards using energy* [21]. By this point of view, one of the useful information is acceleration signal to extract the interesting features.

Khalid and Natl in [12] presented an approach which is based on DFT technique for clustering and classifying spatio-temporal object trajectories by a neural network learning algorithm. Then they used the Fourier coefficient feature to recognize similar motion patterns.

Shir et al. in [25] presented an approach to recognize five kinds of human motion. They used inertial data (accelerometers, gyroscopes) signals which are achieved from an inertial sensor which is attached to a person. Fourier analysis was used to extract the feature from the human motion signal.

Chang et al. in [7] used PS technique as a feature extraction method to classify some periodic human motion from sports video signals. And Rage et al. in [20] proposed a method for human action recognition from video streams that used mean power spectra technique to extract interested features from the bounding boxes which contained the silhouettes of a human for a number of video frames representing a basic action. These two last works using PS technique, are image-based, but we use 3D data signals as an input for PS technique.

1.2 Outline and contribution

We present a new approach which has an ability to classify human behaviours and actions. Our main contribution is that using frequency domain features from PS technique to reach LMA parameters using Bayesian approach. The LMA parameters which are for describing any human motion, can be useful to classify any human action and behaviour. In the experiment, presents an example of action classification based on Bayesian network.

Section 2 presents the LMA concept and section 3 presents the proposed method for extracting features. Section 4 describes classification part. Experimental results are shown in section 5, and Section 6 closes with a conclusion and an outlook for future works.

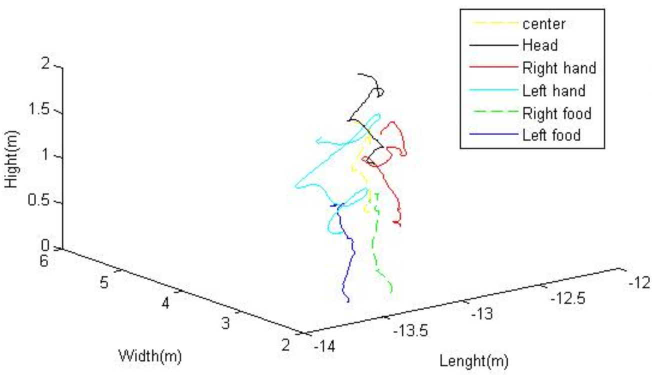

Figure 1: Some sequences position of the 6 body parts for running action in 3D view.

2 Laban Movement Analysis concept

To describe and interpret human motions, there are several notation systems such as *Beauchamp-Feuillet Notation, Benesh Movement Notation, Dance Writing, Eshkol-Wachman Movement Notation* and Laban movement analysis which includes different features to present different human motions precisely [22]. Thus, researchers attempted to use the advantage of these notation systems to understand human motion, in different aspects.

LMA is a well-known system to notate and understand human motions. It comprises five components (*Body*, *Space*, *Effort*, *Shape* and *Relationship*) to describe human motion in different approaches. Researchers attempted to formulate the LMA parameters to be practical to understand human actions by an intelligence system such as [29, 23, 8, 3]. By having LMA parameters, it can be possible to understand different human motions in different aspects. Almost all of the previous works used just some of the components to understand human actions. In this paper, a Bayesian approach which is used the advantage of Effort component properties to understand human actions and behaviours is presented that can be extended to use the other features, LMA parameters and actions related to the application.

Effort component tries to estimate power of human motions. For example, an action can be occurred suddenly or sustainedly, lightly or strongly , etc. Acceleration signal from human body is one of the best features that can be used to sense human motion in *Effort* aspect. Our idea to extract features from acceleration signals can be seen in the next section. In this paper, *Effort.time* component which has 2 states $\{$*Sustained* and *Sudden*$\}$ is used for six body parts to classify some performed actions.

3 Feature Extraction

Fast Fourier Transform (FFT) and PS techniques are the known methods for feature extraction of a signal sequence data. FFT is an advantageous method for processing of frequency domain and analysing spectrum, and PS which derives from FFT answers the question "how much of the signal is at a frequency"[9]. There are some literatures which used these techniques to achieve some features for different purposes related to human motion detection.

In our case, a new method is prepared to extract some features from acceleration signals of six body parts (head, right hand, left hand, right foot, left foot and centre of the body) which are achieved by a motion tracker suit as can be seen in Fig.1. These parts of body are more representative of human motions.We used the advantages of the power spectrum technique for feature extractions.

By having a signal data, its Fourier series should be calculated to estimate the PS of the signal [9]. If f(t) is a finite-energy signal (such as acceleration signals), the Power spectrum $\Phi(\omega)$ of the signal can be achieved by:

$$\Phi\left(\omega\right) = \left| \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f\left(t\right) e^{-i\omega t} dt \right|^2 = \frac{F\left(\omega\right) F^*\left(\omega\right)}{2\pi} \quad (1)$$

where ω denotes the angular frequency and $F(\omega)$ is the continuous Fourier transform of $f(t)$, and $F^*(\omega)$ denotes its complex conjugate. If the signal is discrete with values f_n, over an infinite number of elements, we still have an energy spectral density:

$$\Phi\left(\omega\right) = \left| \frac{1}{\sqrt{2\pi}} \sum_{-\infty}^{\infty} f_n e^{-i\omega n} \right|^2 = \frac{F\left(\omega\right) F^*\left(\omega\right)}{2\pi} \quad (2)$$

Using Eq.3, 3D acceleration signals are calculated from the recorded data achieved by a motion tracker suit which provides a sequence acceleration for each part of the body in x, y, and z coordinate ($f_n(x)$, $f_n(y)$ and $f_n(z)$), separately.

$$f_n = \sqrt{\left(f_n(x)\right)^2 + \left(f_n(y)\right)^2 + \left(f_n(z)\right)^2} \quad (3)$$

The PS signals of the 3D acceleration sequence data can be calculated by Eq.2, as can be seen in Fig.2 a sample of PS signal of an action.

For obtaining features from FFT or PS signals, There are several literatures to provide an approach which attempted to collect some coefficients (peak) of the extracted signals,

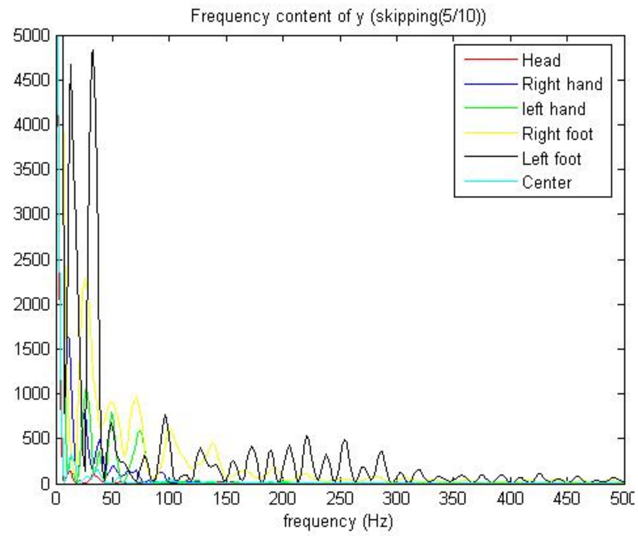

Figure 2: A sample of PS result of 3D acceleration signal of the 6 body parts for skipping action

like [25] which collected first ten coefficients of each FFT result, however they just used one motion tracker which can not present different human motions. But in this paper, we present another approach by dividing the frequency domain of PS signal of six body parts to some small domains to process more information and decrease the effect of possible noise. As [20] mentioned, the power of the PS signals for human motions usually are high in low frequency domains, so the domain frequency segmented in eleven subdomain frequencies. But in low frequency domain, our segmentation size is smaller than in the high frequency domain as can be seen in Fig.3. Moreover maximum of the content (power) of each frequency subdomain can be calculated. Thus, eleven features (maximum) for six body parts are defined to be use for classification of various actions:

$$F = Max\left\{ {}^{Acc}f_i^{pb} \right\},$$

where the *pb* denotes set of body parts, *Acc* denotes the acceleration signal data and $Max\left\{ {}^{Acc}f_i^{pb} \right\}$ denote the maximum content of each *i* subdomain frequency of acceleration signal for each *pb*. The set of *pb* and *subdomain frequency* are as follows:

pb={Head, Left hand, Right hand, Left foot, Right foot, Body center}

subdomain frequency ={(0 - 10), (11 - 20), (21 - 30), (31 - 40), (41 - 50), (51 -100), (101 - 150), (151 - 200), (201 - 300), (301 - 400), (401 - 512)}

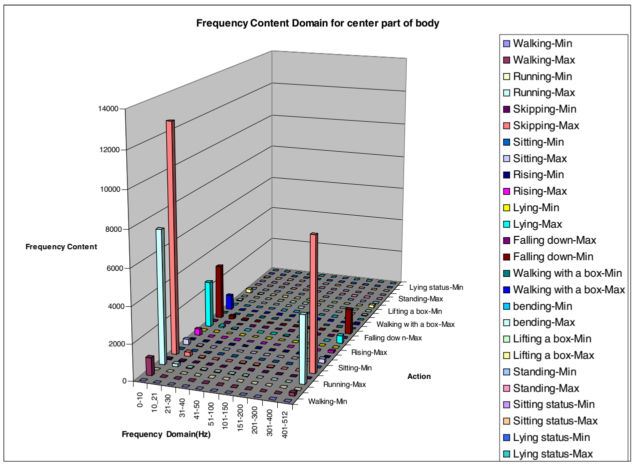

Figure 3: A histogram for a body part, that is showing the definition of some frequency subdomains on the power spectrum signals and minimum and maximum content of each frequency subdomain for each action separately.

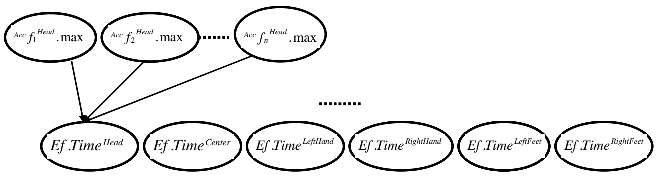

Figure 4: Bayesian Net for LMA parameters classification

4 Bayesian-based LMA and Action Classifications

Feature extraction is applied only once during the training phase for each interested action. The next step is using Bayesian technique in 2 levels. The first level is for classification of LMA parameter by LLFs, and the second one is for classification of some actions by the LMA parameters. Fig.4 is presenting the Bayesian net of the first level. In this Bayesian net set we provide for the six body parts, six parallel Bayesian net which are independent. In Fig.4, each LLFs which are from $\{Max\left\{ {}^{Acc}f_i^{pb} \right\}\}$ has 4 states {No, Low, Medium and High} which are obtained by some thresholds definition. $Ef.Time^{pb}$which denotes *Effort.time* component for *pb* body part, that has two states, *Sustained* and *Sudden*. In this step, LLFs level can have more features like velocity and curvature. In the LMA level, we can define more parameters which can be achieved by the LLFs.

The second level of Bayesian net as can be seen in Fig.5, the LMA parameters are as inputs to classify human actions. The action set can be defined based on the application. Therefore more LMA parameters should be defined depending on the variety of action set.

In this paper we used just first four elements (the subdomains of PS of acceleration signal) which are included most of useful data, as input to the first level of Bayesian net to simplify the system. As can be seen in Fig.6, the idea to join

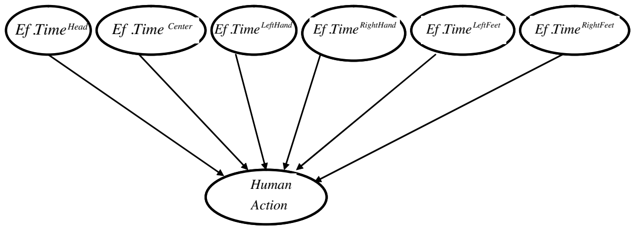

Figure 5: Bayesian Net for action classification

$$
\text{Program}\begin{cases}
\text{Desc.}\begin{cases}
\text{Sp.}\begin{cases}
\text{Relevant variables:}\\
pb=\{Head, Body\_Center, Left\_hand, Right\_hand, Left\_foot, Right\_foot\}\\
f_1^{pb} f_2^{pb}, f_3^{pb}, f_4^{pb} \in \{No, Low, Medium, High\},\\
\mathrm{Ef}_{time}^{pb} \in \{sustained, sudden\}\\
, \mathrm{Action} \in \{walking, running, falling, s\tan ding, ...\}\\
\text{Decomposition:}\\
\mathrm{P}(\mathrm{Action} \prod_{p\in\{pb\}} \mathrm{Ef}_{time}^{p}\ f_1^{p}\ f_2^{p}\ f_3^{p}\ f_4^{p}) =\\
\prod_{p\in\{pb\}} \left(\mathrm{P}(f_1^{p})\,\mathrm{P}(f_2^{p})\,\mathrm{P}(f_3^{p})\,\mathrm{P}(f_4^{p})\,\mathrm{P}(\mathrm{Ef}_{time}^{p} \mid f_1^{p}\ f_2^{p}\ f_3^{p}\ f_4^{p})\right) \mathrm{P}(\mathrm{Action} \mid \prod_{p\in\{pb\}} \mathrm{Ef}_{time}^{pb})\\
\text{Parametric forms:}\\
\mathrm{P}(f_1^{pb})\\
\mathrm{P}(f_2^{pb})\\
\mathrm{P}(f_3^{pb})\\
\mathrm{P}(f_4^{pb})\\
\mathrm{P}(\mathrm{Ef}_{time}^{pb} \mid f_1^{pb}\ f_2^{pb}\ f_3^{pb}\ f_4^{pb})\\
\mathrm{P}(\mathrm{Action} \mid \prod_{p\in\{pb\}} \mathrm{Ef}_{time}^{pb})
\end{cases}\\
\text{Ident.:}
\end{cases}\\
\text{Questions:}\\
\mathrm{P}(\mathrm{Action} \mid f_1^{pb} \wedge f_2^{pb} \wedge f_3^{pb} \wedge f_4^{pb})
\end{cases}
$$

Figure 6: Bayesian program

the LLFs to the LMA parameters and the LMA parameters to the defined actions are presented by a Bayesian program.

5 Experiment

The experiments are done in two steps. At the first step, the data is collected for each action separately by an actor. The actor is not restricted to perform the actions in a predefined time length. We attempted to apply our method to understand sequence of human actions through a long signal data which can be included different actions. For this reason, we need to define a window-frame on the signal, because if we have two actions like *"standing"* and *"falling down"* together in our process of classification, the system will detect just *"falling down"* action, but we will lose the *"standing*". So a one second window-frame which moves on the signals by half of second was defined, that is a common rule to don't lose information through the long signal data. To get more reliable result, the learning dataset is provided by one second of most representative part of each action sample.

By this situation, we obtained learning information which is the probability of LLFs and *Effort.time* component for each body part by more than 100 different collected samples (human actions).

For applying the Bayesian net we need to discretize the PS content . Thus, based on the training data, several

	Walking	Running Skipping Falling Down	Rising Sitting Bending	Standing	Total	Percent
Walking	**9**	**30**			**39**	**23%**
Running Skipping Falling Down	**1**	**114**			**115**	**99%**
Rising Sitting Bending		**2**	**69**	**9**	**80**	**86%**
Standing				**90**	**90**	**100%**

Figure 7: Classification result

thresholds are defined:

$$
f_i^{pb} = \begin{cases}
No & Max\left\{^{Acc}f_i^{pb}\right\} <= 10\\
Low & 10 < Max\left\{^{Acc}f_i^{pb}\right\} <= 80\\
Medium & 80 < Max\left\{^{Acc}f_i^{pb}\right\} <= 300\\
High & Max\left\{^{Acc}f_i^{pb}\right\} > 300
\end{cases}
$$

where f_i^{pb}denotes the discretized of the PS data of *pb* body part in *i* subdomain frequency.

Then, a free Bayesian toolbox which provided by Kervin Murphy and Berkeley [14] is used. Based on the Bayesian net (Fig.4) the Effort.time probability of each body part given the LLFs are achieved separately.

In the second step, we have the probability of *Effort.time* for the six body parts (which are inputs for the second Bayesian net (Fig.5)). Then, the learning information which is the probability of each action given the *Effort.time* component of the six body parts is obtained.

The proposed method is applied on about 100 collected samples. Based on the *Effort.time* component, we can expect to detect the actions which can occurred: Suddenly or Sustainedly. This kind of category is usually useful in surveillance systems that most of the abnormal actions happen suddenly like running or falling down. As can be seen in the result in Fig.7, for some actions the results are considerable, but for*"walking",* its result is not acceptable, because of the thresholds which we defined for discretizing, and the selected LMA feature was not enough to describe it. It shows that for understanding some actions, depend on those actions, some related LMA parameters should be used. For instance, to classify *some* actions, some spatial features to distinguish them are needed. These features are rely on other components of LMA like *Space*, *Body* and *Shape*. For example, by having just height variation of human body which belongs to *Body* and *Shape* components, we can easily distinguish *rising* from *sitting* actions and *running* from *falling down*.

6 Conclusion and future work

In this paper, we presented a 2-step probabilistic approach to understand human actions and behaviours based on the LMA descriptor and using features which are extracted by PS signal of using 3D acceleration data. Bayesian network is applied in two levels. The first level is to obtain the LMA parameters and the second one is for action understanding part. The idea is that the first level is a primitive step which can describe human motion in detail. By having this description of human motion, everyone can use his interesting descriptions to understand human behaviour instead of dealing with LLFs. The idea of selecting these features comes from the concept of LMA.*Effort* component. The *Effort* component is relied on the power of body parts during human motion. Acceleration signals from six body parts are used to estimate different types of actions in the *Effort.time* aspect which represent human body parts motions in terms of type of the motion (sudden or sustained). For extracting the features from acceleration signals, PS technique is used. The results which were provided by Bayesian approach, prove that the approach is sufficient to detect different actions, but we need use more LMA parameters to recognize more complex actions. In future works, we intent to apply our method base on the multi-modal and multi-layer homography framework such as [1] which can give the interested features base on a probabilistic method. Also by applying more LMA features in different aspects, we intent to improve the result in some complex scenarios.

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