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Developing a Motion Language: Gait Analysis from Accelerometer Sensor Systems

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***Abstract*—This work concerns the use of human movement classification as a tool for monitoring and supporting elderly life. The "motion language" methodology is a movement classification technique which aims at generalizing movements and providing easy interpretation of motion signals by decomposing activities into elementary building blocks referred to as "motion primitives". The use of motion primitives to classify motion from visual data has been studied. This work shows that the motion language methodology can be applied to acceleration signals, contributing to the development of wearable monitoring systems. This paper explains the development of the motion language and its use in a gait analysis study. Preliminary results show that the motion language methodology can be used to quantitatively measure gait parameters. In addition, motion primitives are shown to express static and dynamic characteristics of gait patterns and were used to calculate a new symmetry index.**

I. Introduction

The world's population is expected to age considerably in the next 50 years [1]. Projections show that by 2050 the elderly population (aged 65 or over) will grow from 16% to 28% of the total population of Europe (Table I). This change in demographics is mostly due to the increase in life-expectancy and the aging of the Post-World-War-II baby boomers. Today's health care system will struggle to cope with the increased demand of age related care in the coming 50 years.

Table I
Projections of the percentage of the population aged 65 or over in different regions.

Year	2005	2030	2050
World	7.3%	11.7%	16.2%
Europe	15.9%	22.6%	27.6%
Sweden	17.2%	22.8%	24.1%
UK	16.1%	21.6%	24.1%
US	12.3%	19.4%	21.0%
Japan	19.7%	2%	24.1%

Some ways of relieving the health care system from the extra load are: to focus on preventive care, to support aging at home by ensuring safety and assistance in activities of daily living, and to aim at early diagnosis of common conditions. The health and safety of an elder at home may be monitored by intelligent systems which share relevant information with medical personnel and informal care-takers, such as family members and friends. Movement analysis is a powerful and intuitive way of determining a subject's health and functional status [2]. Gait analysis, in particular, provides relevant information about physical and cognitive decline [3].

Many studies have focused on movement recognition for evaluating balance, e.g. [4], and classifying gait, e.g. [5]. Such studies, however, are based on template matching techniques and they have been useful for detecting only a few predetermined activities or events. Another approach to movement classification is decomposing activities into small building blocks referred to as "motion primitives". Motion primitives can be organized through rules into a "motion language".

This work applies the motion language methodology to acceleration data in order to extract gait parameters and describe dynamically different walking patterns. Stride times were calculated, and a new measure of symmetry was derived from the motion primitives. The symmetry index proposed in this work is more informative, and its interpretation is more intuitive, than the traditional symmetry index.

This paper is organized as follows: related work is discussed in Section II; the motion language methodology is explained in Section III; the gait analysis study is presented in Section IV; results are analyzed in Section V; future work is discussed in VI; and Section VII concludes this paper.

II. Related Work

A. Gait Analysis

Gait analysis is an important tool for the diagnosis and evaluation of many conditions. Previous studies have shown that changes in gait can be related to physical and cognitive decline [6] due to aging or illness [7], [8]. Common causes of gait abnormalities in senior citizens include neurological diseases, arthritis and acquired foot deformities [9]. Stroke survivors also frequently display gait abnormalities [10].

Gait analysis has been evaluated for predicting the risk of developing dementia and, in particular, the risk of developing Alzheimer's disease [9]. Another study [11] has quantified that a 1-second increase in time to walk 30ft, when compared to control subjects, can be indicative of an increased risk of developing permanent cognitive impairment. The correlation between slowing of gait and mild cognitive impairment is also supported in [12]. In addition, gait analysis may help identify and quantify the risk of an elder falling [13], and it is an essential tool in the treatment and evaluation of cerebral palsy patients [14], [15]. Gait analysis is also important when fitting prosthetic or orthotic devices, and when evaluating the success of an orthopedic surgery, e.g. a hip-replacement [16], [17].

Gait analysis is already widely used for clinical assessment, but it is often subjective or constrained to a laboratory environment. Motion capture (mocap) systems, in combination with force-plates, provide very accurate descriptions and models of gait. However, these expensive systems must be installed in appropriate rooms and can only be operated by specially trained personnel. Mocap systems can only record movements performed in a small area of the room. Logging long walks is therefore only possible if the patient is walking on a treadmill, which may change the patient's normal gait. Other measuring systems used in the lab setting, more mobile but less informative, are pressure sensitive mats [18]. They provides static spacio-temporal data, like footprints over time, but do not provide dynamic information about *how* the patient's foot is moving in space.

When measuring systems are unavailable, gait and balance are commonly assessed using "time up and go" tests (TUG) and/or grading scales [19], [20]. However, studies have shown that these tests can be subjective and sometimes inconsistent, especially when the tester is inexperienced [21]. Another drawback of current approaches to clinical gait assessment is that tasks performed in the lab do not always represent normal daily activities; as such, they might not provide information about how the subject normally walks. There is, therefore, a clear need for an inexpensive, unobtrusive and easy-to-use system, which allows quantitative analysis of gait patterns outside the lab. In this scenario, wearable sensor systems, composed of inertial sensors such as accelerometers and gyros [22], are particularly useful. Wearable sensor systems certainly overcome the mobility issue, and they are preferable to visual data, since people may feel uncomfortable being recorded by camera-like devices.

Different combinations of inertial sensors have been used, e.g. [23]–[25].

B. Wearable Sensor Systems

A large number of sensors is inconvenient for most long-term monitoring applications. In addition, when designing wearable systems, a clear trade off is observed between mobility and ease of use in terms of: power consumption, autonomy, placement, patient compliance, and data analysis, to name a few. Therefore, one approach to developing new portable sensor nodes is to start with only one type of sensing device and investigate how much information it can gather.

Accelerometers are suitable sensors for wearable systems since current enhancements in micro-electro-mechanical systems (MEMS) technology have made possible the manufacture of miniaturized, low power, low cost accelerometers [22], which are useful for logging human motion data for long periods of time in uncontrolled environments. Accelerometers have been employed for many different purposes: estimating metabolic energy expenditure [26]; monitoring activity [21]; assessing standing balance [4]; detecting falls, postural orientation and classifying activities [2].

Gait analysis studies from accelerometer sensor systems may be divided into three main categories:

1) The reconstruction of movements in space, e.g. [23], [27]. These studies make use of two or more sensors on the same limb in order to reconstruct its trajectory in space and, as such, are not comparable to our work.
2) The detection of gait phases and evaluation of temporal parameters, e.g. [28]–[30]. These studies focus on detecting events such as heel-strike or stance and use this information to calculate stride times, variability, temporal symmetry, etc. They do not, however, provide any information about the way in which the person is walking, i.e if the person's feet are moving according to different trajectories in space.
3) The classification of walking patterns, e.g. [5], [31]. These studies aim at determining if the subject is walking up or down stairs, running etc. They do not, on the other hand, look into single steps and the phases of gait.

The motion language methodology proposed in this work aims at both tasks: identifying the phases of gait, and describing the dynamics of the walking pattern.

III. Motion Language

A fundamental problem in detecting and recognizing human movements is that of representation. Movement classification has traditionally been achieved through some form of template matching or pattern recognition, after manual segmentation and/or statistical feature modeling. These methods require manual labeling of the data, which is labor-intensive and error-prone [32].

The motion language methodology aims at identifying an "alphabet" of elementary motions, which are like building blocks for human movements [33]. This motion alphabet enables the creation of a "motion language", where analogies are made between movements and words. The relationship between action and language is supported by the Mirror Neuron Theory [34] which states that the same brain mechanisms are activated regardless of whether actions are being performed or observed [35].

A motion language is able to generalize movement by describing innumerable concepts using different combinations of a limited number of primitives. The organization of elementary actions for classifying human movement by describing a hierarchical model has already been studied [36]. The concept of motion primitives was also explored in a method which automatically derived vocabularies of movement modules from visual data by taking advantage of the underlying spatial-temporal structure of human movements [32]. Video image sequences have been converted into strings containing sequences of symbols, each representing a manually determined primitive, to classify five one-arm movements [37]. Also from video images (mocap database), the inference of sequential and parallel grammar rules to describe human movements has been studied [38].

Based on previous approaches, the development of a motion language may be divided into four general tasks: Segmentation, Feature Extraction, Symbolization and Grammar Inference. Together, these four tasks constitute the motion language methodology.

A. Segmentation

One of the challenges in the process is determining how to automatically segment the signal into suitable building blocks. Ideally, the signal should be segmented according to its inherent characteristics in order to maximize the amount of information the symbols retain from the original signal. A previous work made use of angular displacement and first-derivative signs to segment the data into four quadrants, each quadrant corresponding to a symbol [38]. This partitioning, however, did not look for the informative characteristics of the original signal; it is, thus, considered artificial. Another work considered the variance of the signal [39], but the segmentation was designed only for movements involving maneuvering objects.

B. Feature Extraction

After segmentation, various features extracted from each segment of the signal are used to classify them into different symbols. The most common approach when detecting daily activities from accelerometer data is to extract information from equally sized sliding windows. This does not take primitives into consideration but rather statistical information about the whole movement.

C. Symbol Assignment

The features extracted from the segments are used to differentiate them from one another. Segments with similar characteristics may be assigned one symbol. Finding appropriate features is important to the creation of relevant symbols. The larger the variability of a given feature, the more symbols will be needed to express different segments, and the more similar segments belonging to the same symbols will be. These symbols are comparable to letters in an alphabet. They may be used to form "words" and "sentences".

D. Grammar Inference

Grammar rules express how symbols may be put together to form words and sentences which represent different movements. They may be inferred from a large collection of data or designed based on known characteristics of the system, e.g. the human locomotive system. Although segmentation, feature extraction, and symbol assignment may not relate directly to movements, the physical limitations of the body should be reflected by grammar rules on syntactic and semantic levels. Syntactic analysis is concerned with deriving rules about which movements are possible, such as "arms only bend one way". Semantic analysis considers rules about how different movements are associated. Humans cannot, for example, "chew gum and whistle at the same time". The elaboration of grammar rules from mocap data has been explored in [38].

None of the motion language approaches mentioned previously have been applied to acceleration data only. The development of a motion language, used to analyze gait from acceleration data, is presented in the following section.

IV. Gait Analysis Study

The goal of this study was to apply the proposed motion language methodology to acceleration data in order to detect heel-strike, toe-off, stance and swing; and use these parameters to identify different walking patterns. *Stance* is defined as the period when the foot is on the ground; *swing* is when the foot is off the ground; *toe-off* is the moment when the foot leaves the ground and *heel-strike* is the moment when the foot meets the ground. *Stride* is the complete sequence: heel-strike, stance, toe-off, swing and heel-strike.

A. Experimental Setup

Two SHIMMER sensor nodes (shimmer-research.com), composed of tri-axial accelerometers, were attached to both shins of the subjects, close to the ankles. The placement of the sensor was chosen so that the user would be able to strap the sensors on without much precision. The movements were sampled at 50Hz and the data was continuously streamed via Bluetooth to a nearby computer. The data was filtered with a mean filter three samples wide. The subjects walked a straight line on a six-meter-long Gold Gait Rite pressure mat [18], which samples data at 60Hz. The data obtained from the pressure mat was used as a reference for swing and stance.

Seven subjects participated in the experiments. They were asked to walk at a comfortable self-paced speed, then at a very slow speed taking shorter steps, and finally, the subjects had their right knee immobilized with a brace in order to simulate limping. Three runs of each type of walk were performed. The number of steps recorded varied from around 10, for normal and limp walking, to around 30, for slow walking. Only steps with good reference data were considered. The data was analyzed and the results obtained from one subject's data are presented in Section V.

B. Motion Language Design

The acceleration signals used in this study were not calibrated to m/s^2 hence the acceleration units will be omitted. In longer data collection sessions, sensors might exhibit drift, in which case some form of adaptive calibration would be required.

The motion language methodology was implemented as follows:

- **SEGMENTATION**: The Segmentation task was performed on the resultant acceleration signal:

  $$A_{res} = \sqrt{A_x^2 + A_y^2 + A_z^2},$$

  where A_{res} is the resultant acceleration, and A_x, A_y, A_z are accelerations in the accelerometer's local coordinate system. When the subject is standing still, with both feet together, x corresponds to the vertical axis, y corresponds to the horizontal axis perpendicular to the direction of walking, and z corresponds to the horizontal axis along the direction of walking.

The chosen segmentation method was a bottom-up linear segmentation algorithm described in [40]. The algorithm starts by fitting a small line segment over every consecutive three samples and iteratively fits longer line segments over neighboring samples until the mean square error (MSE) between the original resultant acceleration and the linearly segmented signal reaches a predetermined error threshold. The data points between start and end of each fitted line are regarded as a segment.

The output of the Segmentation task is illustrated in Figure 1. The diamond-shaped markers indicate the beginning and the end of each segment. The dotted line represents the resultant acceleration before segmentation and the solid line represents the line segments found after segmentation.

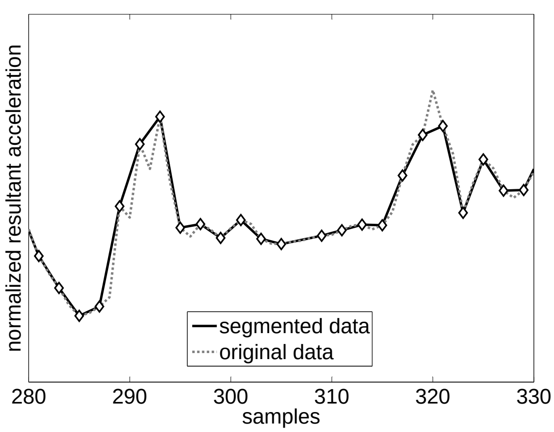

Figure 1. Segmented signal compared to original resultant acceleration signal, for “normal walk”.

- **FEATURE EXTRACTION**: The features extracted from each segment were: variance of the resultant acceleration, var; mean acceleration on all three axes, $\bar{A}_x$, $\bar{A}_y$, $\bar{A}_z$; and the number of samples in the segment, $length$. These features were chosen since they represent well the data in each segment (mean and variance) and its duration (length). The ith segment is then represented by the four-dimensional vector:

$$S_{feat}(i) = [\bar{A}_x(i)\ \bar{A}_y(i)\ \bar{A}_z(i)\ var(i)\ length(i)]$$

- **SYMBOL ASSIGNMENT**: The segment features extracted from the acceleration signal for both the right, S_{featR}, and the left foot, S_{featL}, were divided by their maximum values and normalized to the interval [0 1]. Considering N segments from the right foot and M segments from the left foot, the data is organized in a $(N + M) \times 4$ matrix:

$$\begin{pmatrix} S_{featR}(1) \\ S_{featR}(2) \\ \vdots \\ S_{featR}(N) \\ S_{featL}(1) \\ S_{featL}(2) \\ \vdots \\ S_{featL}(M) \end{pmatrix}$$

The rows of the matrix above (segments) are divided into different groups using k-means clustering. The optimum number of clusters was chosen based on the minimum Davies-Bouldin index [41]. A different symbol was assigned to the segments within each cluster. For simplicity, the symbols are integers contained in the interval between 1 and the maximum number of clusters.

- **GRAMMAR INFERENCE**: The rules describing the symbol sequences were manually derived based on the repetitiveness of the signal and the characteristics of the system, e.g. toe-off can only come between stance and swing, etc. The rules were used to identify four gait parameters: heel-strike, toe-off, swing and stance. Although only two parameters are needed to determine the other two, i.e. either toe-off and heel-strike or stance and swing, all four parameters were estimated individually so recurrent rules could be designed to maximize the accuracy of the classification. The rules were chosen to be subject and gait type specific. In the case of normal walking, for one subject, for example, the designed rules were:

  1) symbol 5 $\Rightarrow$ swing
  2) symbol 3 $\Rightarrow$ stance
  3) transition from symbol 4 to symbol 1 between swing and stance $\Rightarrow$ heel-strike
  4) transition from symbol 2 to symbol 4 between stance and swing $\Rightarrow$ toe-off

  An algorithm may be designed to find these rules automatically by analyzing every symbol and transition, and matching those to known characteristics of the system, e.g. a complete stride is a sequence of heel-strike, swing, toe-off and stance; swing is approximately 40% of the total stride time; hee-strike and toe-off usually cause large acceleration along the vertical axis, etc.

C. Extracting Gait Characteristics

Heel-strikes identified with the proposed motion language methodology and heel-strikes obtained from the reference signal were used to calculate stride times. Gait symmetry was calculated from these stride times. This gait measurement is important when assessing, e.g, rehabilitation after stroke. A commonly used measure of symmetry [42] is:

$$SI = \frac{T_R - T_L}{\frac{1}{2}(T_R + T_L)} 100,$$

where T_R is the average stride time for the right foot and T_L is the average stride time for the left foot.

The closer the absolute value of SI is to zero, the more symmetric the walk. A negative value indicates that the left foot is, on average, slower than the right foot and a positive value indicates the opposite. A slower stride time, however, does not indicate a more abnormal movement and the "affected" side cannot be determined. The value for this index is unbounded and, in practice, a correspondence between this index and quality of gait is unclear. This measure of symmetry only takes into account the average stride time for each foot, and as such, it does not provide any information about the different movements performed by both feet. If the subject limps but manages to walk with similar stride times, the SI index will not consider this to be an asymmetric walk.

The derived symbols can be used to compute a more informative measure of symmetry which takes all the acceleration data into account, as follows. After substituting the acceleration signal for the respective symbol sequence, histograms of the time elapsed between two consecutive symbol transitions of the same kind are calculated for all possible transitions, i.e. $\{1$ to 1, 1 to 2, 1 to 3, ..., N to $N\}$, where N is the number of symbols (see Figure 2). The symmetry index based on the transition histograms is computed by:

$$SI_{symb} = \frac{\sum_{i,j=1}^{N} \frac{1}{n_{ij}} \sum_{k=1}^{K} |h_{Rij}(k) - h_{Lij}(k)|}{\sum_{i,j=1}^{N} \frac{1}{n_{ij}} \sum_{k=1}^{K} |h_{Rij}(k) + h_{Lij}(k)|},$$

where N is the number of symbols; K is the number of bins in the histograms; n_{ij} is the number of non-empty histogram bins for transition ij, i.e. from symbol i to symbol j; $h_{Rij}(k)$ is the normalized value for bin k in the transition histogram ij for the *right* foot; and $h_{Lij}(k)$ is the normalized value for bin k in the transition histogram ij for the *left* foot.

This index ranges from 0 to 1, where 0 means total *symmetry* and 1 means complete *asymmetry*. SI_{symb} takes into account not only the stride times but also the dynamics of the movement. The SI_{symb} index demonstrates one way in which the symbol abstraction used in the motion language methodology can be used to extract meaningful information from sensor data.

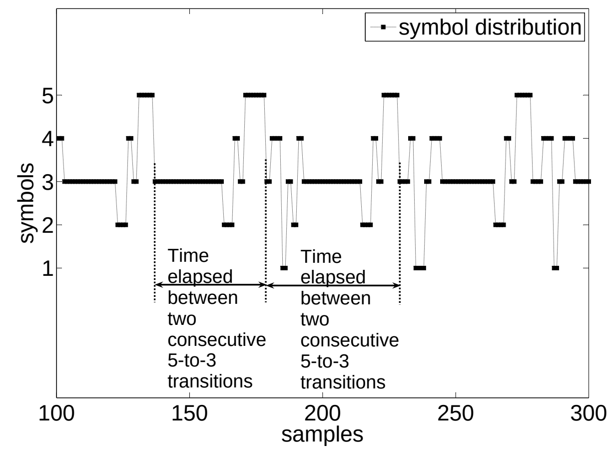

Figure 2. Time elapsed between two consecutive transitions of the same kind (5-to-3). Values found for all such transitions are used to construct transition histograms.

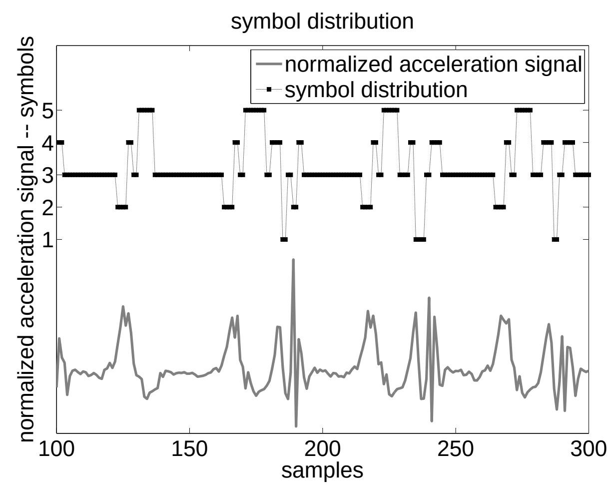

Figure 3. Symbol distribution over time compared to the original resultant acceleration data, for "normal walk".

Table II
NUMBER OF CLUSTERS FOUND IN SYMBOL ASSIGNMENT FOR EACH TYPE OF WALK.

Type of walk	**Normal**	**Slow**	**Limping**
no. of clusters	4	3	9

V. ANALYSIS OF RESULTS

Figure 3 illustrates the symbols found for the normal walk data (right foot) along with the resultant acceleration, and Figure 4 shows the same symbols along with the reference data from the pressure mat. The symbols found for the limp walk data are shown in Figure 5.

The symbols found for "normal walk" and "slow walk" data were very similar and the rules describing gait events were the same for both feet. On the other hand, the symbols found for "limp walk" were very different from one foot to the other. The different symbols, in this case, reflect the asymmetric nature of the walk. In addition, the larger variety of movements, since the feet are moving differently from each other, increased the complexity of the signal and more symbols were needed to describe the walk. The number of clusters found during the Symbol Assignment task, for this particular subject, are shown in Table II.

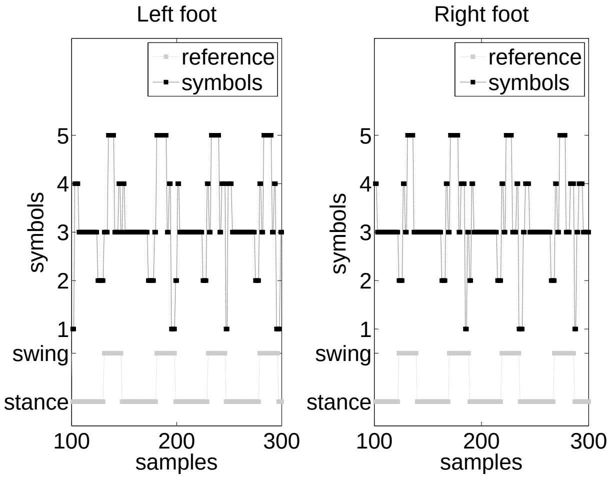

Figure 4. Symbol distribution over time compared to the reference signal from pressure sensitive mat, for "normal walk".

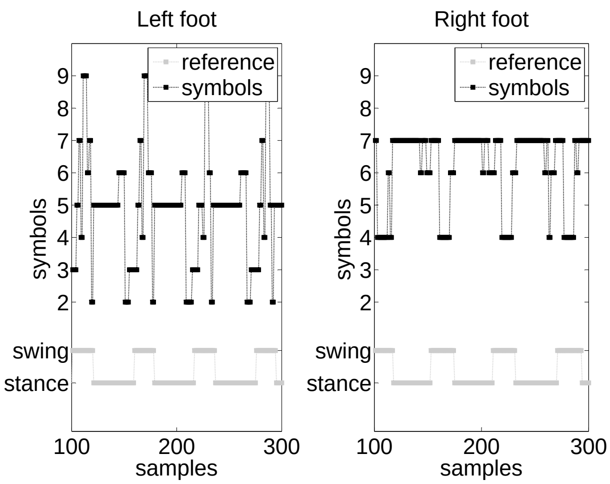

Figure 5. Symbol distribution over time compared to the reference from the pressure sensitive mat, for "limp walk".

Figure 6 illustrates the parameters identified using the proposed motion language methodology, shown alongside the reference signal. The detection of heel-strike and toe-off for the right foot from the normal walk data set are displayed in Figure 7.

The average heel-strike and toe-off detection errors are very small for true positives (see Tables III and IV), and correspond to about 5% of the stride time in the worst case. The false positives and false negatives happened, in general, at the start or end of the data set, where there were no symbols before or after to be inferred from (conditional rules). Future work might avoid this by using longer data sets. Pressure sensitive insoles may be more appropriate than the pressure mat for data collection, since they may provide continuous reference for heel-strike and toe-off for longer periods of time.

The SI and SI_{symb} symmetry indices for all the three types

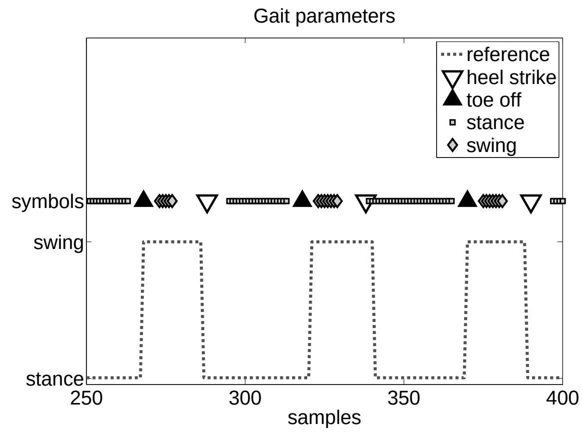

Figure 6. Gait parameters determined from grammar rules after segmentation, feature extraction, and symbolization, for "normal walk".

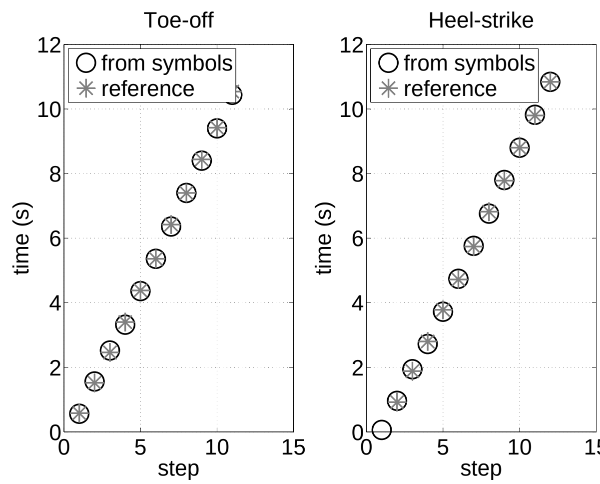

Figure 7. Heel-strike and toe-off detection compared to the reference signal from the pressure sensitive mat, for "normal walk".

of walk are shown in Table V. The same one-second difference in average stride time between feet, for slow walk and limp walk, resulted in different absolute values of SI. The SI index is biased by the stride time. The SI symmetry index found for the limp walk, both from the reference data and from the symbols, is close to zero. This value does not express the asymmetry of the limping pattern. Though the subject was moving each leg differently, the average stride time for both feet was still similar. The SI_{symb} symmetry index, however, picks up on the asymmetry of the limping gait. According to the SI_{symb} index, limping is less symmetric than normal or slow walking, and its value is not biased by the stride time.

Despite the limited amount of data presented here, the relevance of this study lies in the fact that acceleration data was automatically segmented and symbolized. Based on these symbols, a small number of rules was designed, based on previous knowledge of the system, and used to determine relevant gait parameters. The detection of heel-strike and toe-off, and

Table III
OVERVIEW OF THE RESULTS FOR HEEL-STRIKE DETECTION.

Type of Walk	Normal		Slow		Limping	
	Left Foot	Right Foot	Left Foot	Right Foot	Left Foot	Right Foot
no. of Steps	9	11	30	29	12	9
no. of False Negatives	0	0	1	2	1	1
no. of False Positives	0	1	2	1	1	0
Average Error of True Positives (s)	0.03	0.04	0.07	0.04	0.02	0.03

Table IV
OVERVIEW OF THE RESULTS FOR TOE-OFF DETECTION.

Type of Walk	Normal		Slow		Limping	
	Left Foot	Right Foot	Left Foot	Right Foot	Left Foot	Right Foot
no. of Steps	9	11	30	29	12	9
no. of False Negatives	0	0	1	0	0	0
no. of False Positives	0	0	1	2	0	0
Average Error of True Positives (s)	0.03	0.04	0.07	0.06	0.03	0.02

Table V
OVERVIEW OF THE RESULTS FOR SYMMETRY INDICES, SI AND SI_{symb}.

Type of Walk	Normal		Slow		Limping	
	Left Foot	Right Foot	Left Foot	Right Foot	Left Foot	Right Foot
Average stride time (s) (symbols)	0.98	0.98	1.29	1.28	1.17	1.18
Average stride time (s) (reference)	0.98	0.98	1.29	1.28	1.17	1.17
SI **(symbols)**	0		-0.78		0.85	
SI **(reference)**	0		-0.78		0	
SI_{symb}	0.12		0.04		0.95	

the classification of the different phases of gait presented small errors when compared to the reference signal. In addition, the automatically derived symbols expressed different movements that are not easily expressed by temporal measurements, such as stride time. Therefore, this symbolic representation of the signal allowed an intuitive measure of symmetry to be derived, which was more informative than the typical symmetry index.

VI. FUTURE WORK

This study has laid the ground work for a number of further investigations. A more extensive analysis of the data is still to come, which will compare symbols across subjects and attempt to find correspondences between the symbols found for each type of walk. The goal of this next study will be to find symbols robust enough to describe different subjects' gait patterns, and comprehensive enough to span different walking patterns. In addition, an algorithm will be designed to automatically extract rules describing gait parameters, based on pre-knowledge of the system (unsupervised learning).

Three possible paths to finding more informative symbols seem particularly interesting to consider: investigating new segmentation methods; investigating new features and rules; and investigating new clustering and symbolization techniques. New segmentation methods could be based on statistical characteristics of the signal, such as the probability of certain values occurring, or non-linear local descriptions, such as reoccurring sequences of values. New features and rules could exploit the parallelism between feet. In normal walking patterns, for example, both feet should be performing the same activity but shifted in time. Using this information may improve or ease the detection of gait parameters. The third path may investigate the use of system identification approaches and hybrid Markov models to cluster and symbolize the data.

The motion language methodology has been applied to acceleration data, but it can be extended to any time-series. Different types of sensors could undergo the same analysis. This method also provides a good compression of the original signal and can be used to reduce the computational complexity of different techniques in learning or adaptive systems.

VII. CONCLUSION

Most of the research efforts put into detecting and classifying human movements have so far lacked the ability to generalize motion. This work discussed the development of a motion language from accelerometer signals which was used to quantitatively analyze gait parameters and characteristics of different gait patterns.

The proposed motion language methodology consists of representing the original data as a sequence of informative motion primitives, and studying the rules that govern the occurrence of each primitive. Preliminary results show that heel-strike and toe-off instances can be detected accurately with this method. The primitives were used to determine stride times and walk symmetry. In addition, a new symmetry index was proposed to provide temporal as well as dynamic information about gait patterns, which the typical index did not express. This symmetry index based on motion primitives is an example of how the motion language can contribute to the understanding of movements, the interpretation of accelerometer signals, and therefore, the development of wearable monitoring systems.

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