2014 5th IEEE RAS & EMBS International Conference on
Biomedical Robotics and Biomechatronics (BioRob)
August 12-15, 2014. São Paulo, Brazil

Gait event detection through neuromorphic spike sequence learning

Wang Wei Lee[1], Haoyong Yu[2] and Nitish V. Thakor[3]

Abstract— **We present a novel sampling and processing method for detecting gait events from an insole pressure sensor. Inspired by how tactile data is processed in the brain, we propose the use of timing, instead of intensity, as our event detection feature. By sacrificing the need for accurate intensity measurements, it is possible to achieve superior temporal resolution, which is arguably more important given the need for timely feedback. In this paper, we demonstrate temporally accurate gait-event detection of 1.2 ± 7 ms (mean and standard deviation) for heel-strike and 0.2 ± 14 ms for toe-off events compared to the reference system, and a success rate of above 97% in most trials, using only 1 bit of pressure information per channel. Our method thus has the potential to achieve much lower computational complexity and bandwidth, both of which are key to low-cost, portable solutions for prosthetics, exoskeletons or long-term gait monitoring applications.**

I. INTRODUCTION

The detection of gait events is a crucial aspect of gait analysis. Specific events in time, such as heel-strike (HS) and toe-off (TO), are often used as markers for gait segmentation, as they represent the start of stance and swing phases respectively [1]. They are also used for characterization of gait, and the development and evaluation of gait assist devices and sensors. Some examples include functional electrical stimulation (FES) orthoses for foot drop [2], [3] and cerebral palsy toe walking [4], [5], as well as providing feedback for control of robotic exoskeletons and prosthetics in rehabilitation [6], [7]. Although gait events can be identified by trained personnel, the approach is tedious, time consuming and therefore undesirable. The ability to automatically detect and segment gait phases would thus be very useful for such applications.

In clinical gait analysis, the force pressure plate remains the gold standard for detecting gait events [8]. However, force pressure plates are static and unsuitable for constant monitoring of gait events beyond the laboratory environment. They are also susceptible to false positives from weight shifting, since they rely on a single calibrated threshold [9]. Alternatively, gait event detection can also be done using kinematic data [9], [10]. However, gait event detection through kinematic data requires several assumptions to be made. For instance, the maximum vertical and horizontal components of foot acceleration could be used to identify foot-contact and foot-off events [8]. Such assumptions may not be valid for subjects with abnormal gait [5].

[1]Wang Wei Lee is with the Graduate School for Integrative Sciences and Engineering, National University of Singapore, Singapore 119077. lee_wang_wei@nus.edu.sg

[2]Haoyong Yu is with the Department of Biomedical Engineering, Faculty of Engineering, National University of Singapore, Singapore 119077. bieyhy@nus.edu.sg

[3]Nitish V. Thakor is the Director of Singapore Institute for Neurotechnology (SINAPSE) and Professor of Electrical and Bioengineering at the National University of Singapore 119077, and Professor of Biomedical Engineering at Johns Hopkins University, Baltimore, MD 21218 USA. sinapsedirector@gmail.com

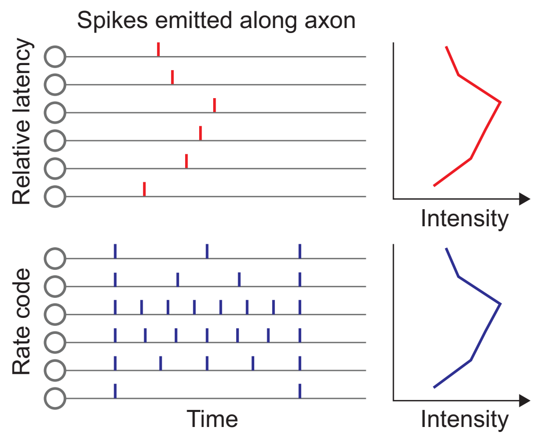


Fig. 1: Illustration of rate code vs. relative spike latency code. Only one spike per receptor is required to encode an intensity profile using latency code, while rate code requires many spikes per receptor for the same profile.

Insole pressure sensors appear to be a good alternative [10]. These devices usually consist of a 2-D matrix of pressure sensors covering the entire insole. However, the need to sample numerous sensing points quickly and accurately, and at the same time processing them within the timing constraints of the application remains a challenge. Commercial sensors which have both high density and high sampling rates remain very costly.

The somatosensory system of the human body faces the same challenges too. Slowly adapting mechanoreceptors (SA-I and SA-II) are known to encode intensity information in their firing rate [11]. The rate code requires downstream neurons to decode the signal via temporal averaging. However, given the fact that mechanoreceptors rarely fire at rates of over 100 Hz, it is unlikely that our brain relies purely on intensity information through rate coding alone, since the decoding process would be too slow. Indeed, researchers have discovered other codes, such as relative spike latency codes, which are used in the processing of visual, auditory, olfactory and somatosensory pathways [12]–[15]. Relative spike latency codes make use of the time difference between spikes in a population response to encode information, and hence can operate with only a single spike per mechanoreceptor (Fig. 1) [16]. This principle can also be applied to artificial tactile sensors.

Implementing such a mechanism requires appropriate encoding and decoding processes. In the encoding step, the

978-1-4799-3127-9/6/14/$31.00 ©2014 IEEE

stimulus has to be converted into spatio-temporal patterns of spikes. This is possible through the use of binary sampling, where a single threshold is used when converting analog signals to digital. Although intensity information is heavily reduced, temporal resolution could be much higher, since the A/D step is essentially implemented by a comparator. Hence, the time of threshold crossing at each sensing point can be accurately determined. Combined with the uneven pressure distribution over time as the stimulus is applied, the relative time differences of these time points can thus carry information unique to the stimulus.

The decoding step involves pattern recognition on the spike patterns. This can be achieved through the use of spiking neural networks. Several supervised algorithms exist. Essentially, a single, fully connected neuron can be trained to produce an action potential when the preferred stimulus is presented. The robustness of such algorithms can be extended through the use of liquid state machines [17], or random postsynaptic kernels [18]. When fully trained, the neurons can perform recognition in real time, and can even be implemented in hardware [19].

In this paper, we demonstrate the use of relative spike time coding for detection of gait events. In our previous paper, we successfully applied the principle to the classification of local curvatures [20]. In contrast to the previous problem, the current application requires the output spike to be temporally precise. To achieve this, we use the Synaptic Kernel Inverse Method (SKIM) [18]. This is a supervised learning rule, where artificial neurons are trained to recognize spatiotemporal patterns of spikes. The role of the neurons are then to emit spikes of their own when their preferred gait events occur, while remaining silent otherwise.

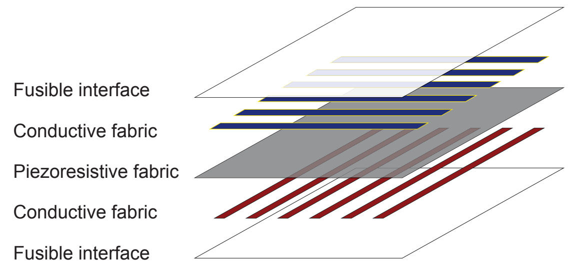
II. Method

A. Fabric insole sensor

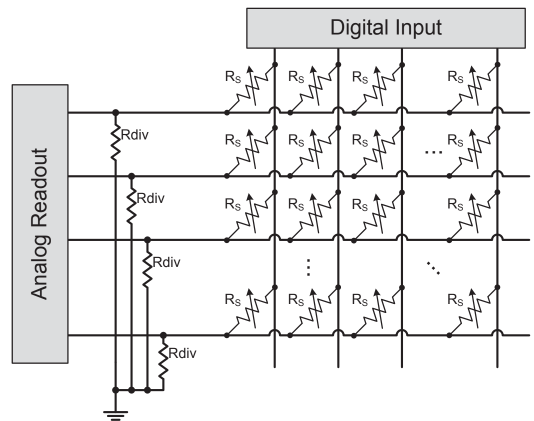
A low cost, foot pressure sensor was made using conductive fabric (Fig. 2a). The construction involves a piezoresistive fabric (NW-SLPA from Eeonyx) sandwiched between two layers of conductive fabric (Silver coated nylon, LessEMF). The conductive fabric forms a row and column matrix, where each intersection between a row and a column constitutes a sensing element. The arrangement is then held together using non-conductive fabric fusible interface.

A standard multiplexed readout circuit was used (Fig. 2b). The final sensor has 92 sensing points and is trimmed to form an insole (Fig. 2c). As the resistance at each intersection decreases with increasing pressure, the pressure at each point is derived by measuring the potential difference across it. This is performed by activating each column *m* with a digital high signal (5 V TTL) while deactivating other rows with a digital low. Each row *n* can then be read using a potential divider circuit, with each reading corresponding to the potential difference at point (*m,n*).

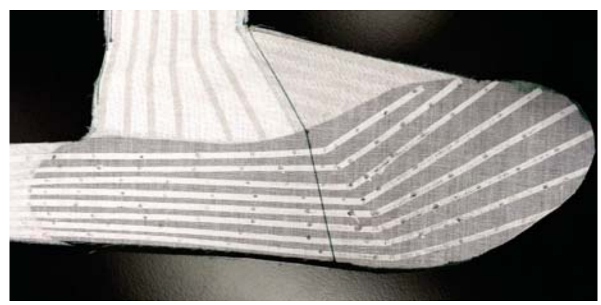
For this paper, R_{div} = 220 kΩ. Each intersection was sampled at a rate of 1 kHz with a 16 bit ADC (USB-6356, National Instruments). Due to the sensor's basic construction, the response varies from point to point. However, there is no need for precise calibration of each point, since our approach relies on temporal changes, not pressure intensity, as we will explain in the subsequent sections.



(a) Layers of the sensor



(b) Readout circuitry



(c) The insole sensor

Fig. 2: Sensor design and readout circuitry

B. Spike conversion

The conversion from analog data to spike output was performed offline in a similar manner as [20]. In essence, a hard threshold θ_i was applied to the analog signal. Subsequently, the signal and its inverse were fed to a phasic Izhikevich neuron [21], with parameters a = 0.002, b = 0.25, c = -65, d = 6, I = 0.6, simulated with 0.1 ms precision. The output from the 184 neurons was then used as the input to the algorithm (Fig. 3). The phasic properties of the neuron has a low-pass effect on the rapid-switching that occurs as a consequence of having a hard threshold.

The main significance of this approach is the fact that the algorithm computes on effectively binary readouts of the sensor, which could be similarly achieved using much

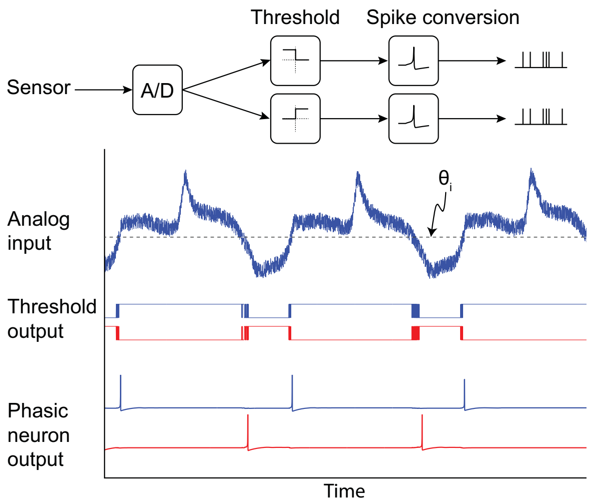


Fig. 3: Illustration of process from analog signals to spikes.

simpler comparator circuits. In this paper, the readout was in analog, with the spike conversion performed offline, as it allows us to understand the effects of various conversion parameters on the final output.

C. *Synaptic kernel inverse method*

First introduced in [18], the synaptic kernel inverse method (SKIM) is a method for solving the weights of a discrete-time perceptron using linear regression techniques. Unlike gradient descent methods, SKIM is not susceptible to being trapped in local minima, and has the advantage of being parameter free. We adopt a two layer spiking neural network architecture in this paper, with $n = 184$ input neurons and a single output neuron per type of gait event (Fig. 4). The input neurons are essentially the Izhikevich spike conversion neurons used in the previous step. We note that in the original paper [18], the authors advocate the use of an additional hidden layer with random kernels and weights to increase the dimensionality of the signal. Our experience with the gait data showed little improvement when the hidden layer is used, and hence we decided to omit it for simplicity.

Before feeding the spikes to the perceptron, a conversion to continuous values is required. We used an alpha kernel:

$$\alpha_n(t) = \sum_{t_n \leq t} \frac{t - t_n}{\tau} \exp\left(-\frac{t - t_n}{\tau}\right) \tag{1}$$

Where t_n are the input spike times, and τ is the time constant of the synapse. The time constant affects the persistence of each input spike, as it determines the length of time which past spikes are still represented since its occurrence. We used $\tau = 20\,\text{ms}$ in this paper. The use of the alpha kernel was simply a matter of choice, and as shown in [18], other kernels are equally applicable.

Since the kernel is static, it is possible to formulate the system as a set of linear equations:

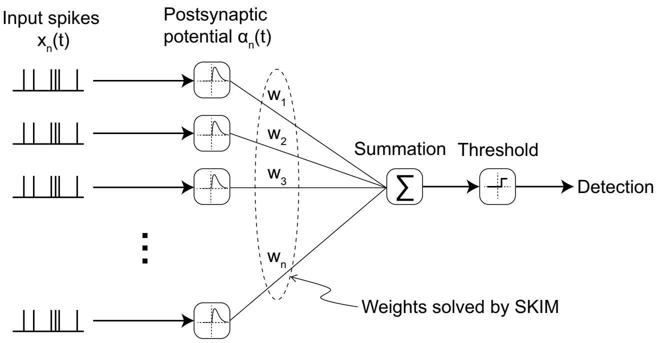


Fig. 4: Event detection using perceptron with weights obtained through SKIM

$$AW = Y$$

$$\begin{pmatrix} \alpha_1(1) & \alpha_2(1) & \cdots & \alpha_n(1) \\ \alpha_1(2) & \alpha_2(2) & \cdots & \alpha_n(2) \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_1(t) & \alpha_2(t) & \cdots & \alpha_n(t) \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_t \end{pmatrix} \tag{2}$$

where:

$$Y \in \{0, 1\}$$

The matrix Y is the reference signal, consisting of binary values that represent a spike or non-spike at each discrete point in time. The weights can then be obtained analytically by taking the Moore-Penrose pseudoinverse:

$$W = A^{+}Y \tag{3}$$

D. *Reference signal*

The SKIM method requires that a reference signal be present in order to solve for the weights. In this paper, the reference signal was obtained using a force pressure plate (AMTI OR6-7-1000, Watertown, USA). Only the vertical component of the ground reaction force was used. A threshold of $5\,\text{N}$ on the rising edge was used to detect the heel strike (HS) event, while the toe off (TO) event was detected on the falling edge at the same threshold (Fig. 5). Thresholds of $2.5 - 20\,\text{N}$ [9], [22]–[24] have been used in various other literature, with lower thresholds giving a closer approximation to the actual event.

The SKIM method tends to suffer from class imbalance when the reference spikes are sparse. This was mitigated by increasing the reference spike width, as recommended by [18]. A spike width of $20\,\text{ms}$ ($\pm 10\,\text{ms}$ from reference) was used in this work (Fig. 6).

III. Experiment

One healthy subject was recruited for this study, and was instructed to perform 90 valid walks on a $10\,\text{m}$ track at a self-selected pace. The force pressure plate was placed in the middle of the track, and the right foot has to land fully within the force pressure plate to be considered a valid

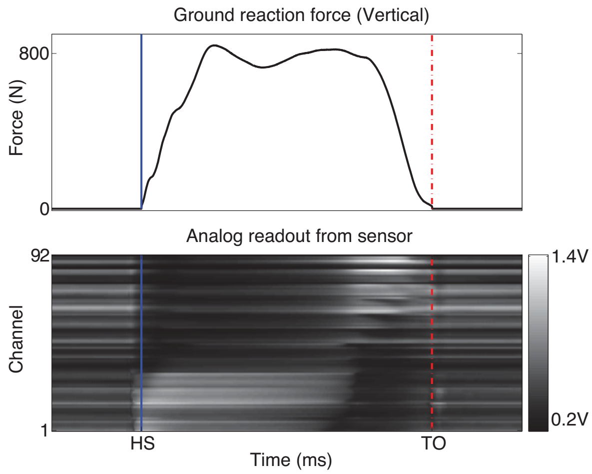


Fig. 5: Raw data from both systems for a single segment.

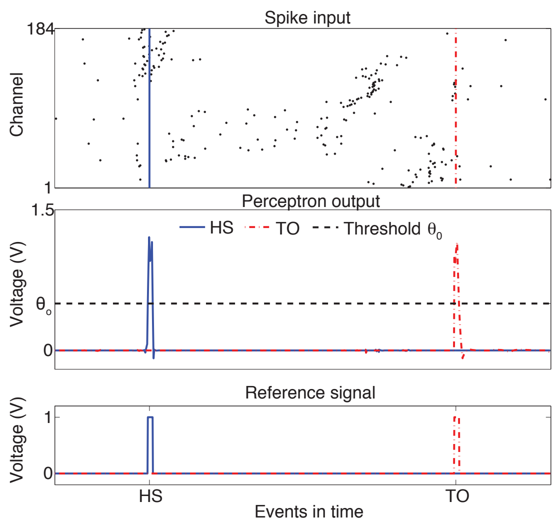


Fig. 6: Detection of events from spiking input. The output threshold θ_o was manually chosen based on the response to training data.

trial. One insole sensor was embedded in the right shoe of the subject. Both systems were hardware synchronized and sampled at 1000 Hz. A Matlab routine was used to automatically segment the force pressure plate and insole data offline into individual steps starting 300 ms before HS and ending 300 ms after TO.

Two output perceptrons were used to detect gait events corresponding to HS and TO respectively. Cross validation was performed by training the perceptrons with 30 steps and validating them on the other 60 steps. The trials were repeated thrice to ensure all steps were used for both training and testing. As the perceptrons are not inherently spiking, further processing was performed to obtain the exact time-point of a detected event. Binary data after threshold was first clustered into groups, with *ones* that are less than 50 ms apart treated as a continuous positive output. The time of detection was then taken to be the start of each group (Fig. 6).

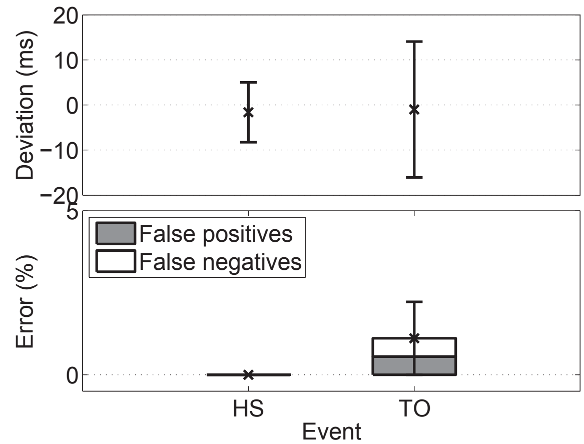


Fig. 7: Accuracy of gait event detection, with sensor threshold $\theta_i = 0.4\,V$. The upper plot indicates the mean and standard deviation of event detection, referenced against a forceplate sensor. The lower plot shows mean and standard error (across 3 cross validation runs) of detection error.

A. Error metric

The algorithm was evaluated by *a*) number of false positives, *b*) number of false negatives, and *c*) temporal deviation of detected events from the reference system. A false positive is defined by an output spike that is not within 100 ms of a reference signal, while a false negative is the failure to emit a spike within 100 ms of a reference signal. Both false positive and false negatives were normalized against the number of steps taken in the test dataset.

B. Results

Fig. 7 shows the results of the experiment. Gait events were detected with a mean and standard deviation of 1.6 ± 7 ms and 1.0 ± 15 ms earlier than the force pressure plate for HS and TO respectively. Detection of HS was more temporally precise as compared to the TO event. Nevertheless, most events were detected within 20 ms of the reference system, which is comparable to other instrumented insoles [10], [25].

The percentage of false positives/negatives remained below 2% on average (Fig. 7). Notably, all HS events were reliably detected. Based on visual observation, this was due to the high repeatability of spike patterns created during HS.

In addition, we evaluated the sensitivity of our approach to the input threshold used. Thresholds of $0.3 \leq \theta_i \leq 0.7$ V (in steps of 0.1 V) were used for conversion of analog to binary signals. The chosen range represents a region where most values fluctuate (Fig. 5).

Comparing the performance across various input thresholds, it is apparent that the temporal accuracy was not significantly affected by the choice of input threshold (Fig. 8 and 9). The average temporal accuracy remained within 2 ms of the reference signal, and this was consistent for all trials. Average detection error was below 3% for TO regardless of input threshold, while all HS events were successfully detected. There is no obvious trend as to how classification error might be influenced by the choice of input threshold.

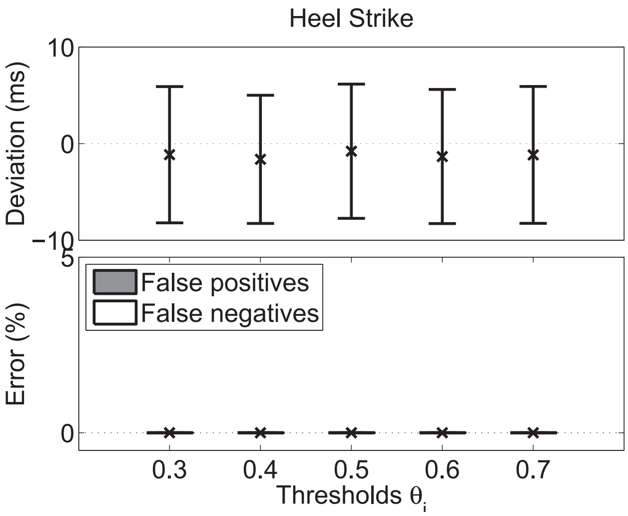


Fig. 8: Comparison of HS event detection accuracy based on input threshold used. Error bars computed similar to Fig. 7.

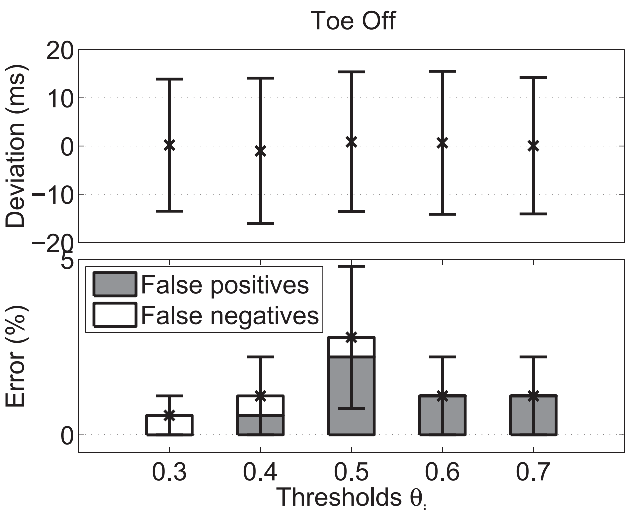


Fig. 9: Comparison of TO event detection accuracy based on input threshold used. Error bars computed similar to Fig. 7.

IV. Discussion

A major bottleneck to large pressure sensing arrays is the low sampling rate and large readout bandwidth required. These requirements are made more stringent on portable wireless platforms, where power, computation and communication resources are further constrained. This is especially so for detecting gait events, where a fully embedded, wireless and low cost system remains elusive. While the performance of micro-processors will no doubt increase in the future, it is also prudent to explore alternative computation methods.

In this paper, we have demonstrated how gait event detection could be achieved using temporal information alone. Through binary sampling, lower bandwidth requirements and higher sampling rates could be achieved without compromising power consumption, should dedicated comparator circuits be used. The use of a fixed pressure threshold may appear to lack robustness, since it is possible for the readout to be saturated throughout the entire gait cycle. Nevertheless, we have shown that the approach works on a range of threshold values, as long as spikes generated are of sufficiently high dimension. It is also possible to derive automated ways of choosing a threshold. The learning process is potentially robust against unnatural gait, as it is data driven and relies only on the accuracy of the reference system. This approach would be especially suited to applications where a low-cost gait detection function is desired.

We are aware that this approach would not satisfy all clinical applications, as it provides only temporal information on when gait events occur. In addition, its performance is also highly reliant on the quality and variety of training data available, which is difficult to obtain in the first place. Moreover, being primarily data driven, the temporal features have little meaning on their own.

Nevertheless, the ability to detect gait events accurately would already be useful in a variety of applications, from gait segmentation to assistive prosthetics. Interestingly, the algorithm is not constrained to the detection of specific gait events, but could be trained to respond to any consistent point of a gait cycle. This may be advantageous to applications such as FES, since FES stimulation protocols are often a function of muscle latency, i.e. the delay between muscle stimulation and production of muscle force [26]. Hence, the optimum time for stimulation may be arbitrary, and not corresponding to any specific gait event. The algorithm could thus be trained to respond at the optimum time, in very much the same way as it is for a gait event.

We note that the design of the experiment is highly simplified, and more tests, including subjects with pathologic gait should be carried out for further verification. The approach should also be validated for walking across multiple terrains. In addition, robustness to false positives during weight shifting, a common problem for instrumented insoles, should be quantified.

A natural progression would involve packaging the setup into a self-contained embedded system, where the advantages of our sampling approach would be more obvious. Such a system would be applicable to a multitude of uses, from personalized long term monitoring in gait rehabilitation to exoskeleton integration.

The exact representation of sensory information in the brain is ill understood. However, the fact that asynchronous spikes are used instead of continuous signals clues us to explore the use of temporal information to encode stimuli. More importantly, it has been shown that multiple sets of information can be multiplexed within the same population of axons across different time scales [27], suggesting that more efficient communication protocols exist through spike representation. Such a neuromorphic approach might bring us a step closer to the ultimate goal of sensory integration with real biological neurons.

V. Conclusion

A gait event detection approach, based purely on temporal properties of pressure signals have been presented. The approach has been demonstrated on a real-life application, using a simple fabric based insole pressure sensor. Despite having only 1-bit of information per channel, our approach demonstrates absolute mean temporal accuracy below 2 ms the reference system, while detection errors are below 3% in most trials. The approach also has very low bandwidth requirements, and is thus suited for embedded applications.

ACKNOWLEDGMENT

The authors would like to thank Kyung-Ryoul Mun and Chan Chow Khuen for their assistance with the force pressure plate reference system, as well as assisting in the experiments conducted.

REFERENCES

[1] J. Perry, J. R. Davids *et al.*, "Gait analysis: normal and pathological function," *Journal of Pediatric Orthopaedics*, vol. 12, no. 6, p. 815, 1992.

[2] A. Mansfield and G. M. Lyons, "The use of accelerometry to detect heel contact events for use as a sensor in fes assisted walking," *Medical Engineering & Physics*, vol. 25, no. 10, pp. 879–885, 2003.

[3] S. Ghoussayni, P. Catalfamo, D. Moser, and D. Ewins, "Experience in the use of a single gyroscope as a sensor for FES foot drop correction systems," in *Proc. 9th Ann. Conf. IFESS Society*, 2004, pp. 398–400.

[4] R. T. Lauer, B. T. Smith, and R. R. Betz, "Application of a neuro-fuzzy network for gait event detection using electromyography in the child with cerebral palsy," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 9, pp. 1532–1540, 2005.

[5] B. Hsue, F. Miller, F. Su, J. Henley, and C. Church, "Gait timing event determination using kinematic data for the toe walking children with cerebreal palsy," *Journal of Biomechanics*, vol. 40, p. S529, 2007.

[6] S. K. Banala, S. H. Kim, S. K. Agrawal, and J. P. Scholz, "Robot assisted gait training with active leg exoskeleton (alex)," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 17, no. 1, pp. 2–8, 2009.

[7] A. J. Del-Ama, A. D. Koutsou, J. C. Moreno, A. De-Los-Reyes, Á. Gil-Agudo, and J. L. Pons, "Review of hybrid exoskeletons to restore gait following spinal cord injury." *Journal of Rehabilitation Research & Development*, vol. 49, no. 4, 2012.

[8] A. Hreljac and R. N. Marshall, "Algorithms to determine event timing during normal walking using kinematic data," *Journal of biomechanics*, vol. 33, no. 6, pp. 783–786, 2000.

[9] M. Hanlon and R. Anderson, "Real-time gait event detection using wearable sensors," *Gait & posture*, vol. 30, no. 4, pp. 523–527, 2009.

[10] S. De Rossi, S. Crea, M. Donati, P. Rebersek, D. Novak, N. Vitiello, T. Lenzi, J. Podobnik, M. Munih, and M. Carrozza, "Gait segmentation using bipedal foot pressure patterns," in *4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob), 2012*. IEEE, 2012, pp. 361–366.

[11] Å. B. Vallbo, R. Johansson *et al.*, "Properties of cutaneous mechanoreceptors in the human hand related to touch sensation," *Hum Neurobiol*, vol. 3, no. 1, pp. 3–14, 1984.

[12] M. Meister and M. J. Berry II, "The neural code of the retina," *Neuron*, vol. 22, no. 3, pp. 435–450, 1999.

[13] T. Lu, L. Liang, and X. Wang, "Temporal and rate representations of time-varying signals in the auditory cortex of awake primates," *Nature neuroscience*, vol. 4, no. 11, pp. 1131–1138, 2001.

[14] J. Perez-Orive, O. Mazor, G. C. Turner, S. Cassenaer, R. I. Wilson, and G. Laurent, "Oscillations and sparsening of odor representations in the mushroom body," *Science*, vol. 297, no. 5580, pp. 359–365, 2002.

[15] R. S. Johansson and I. Birznieks, "First spikes in ensembles of human tactile afferents code complex spatial fingertip events," *Nature neuroscience*, vol. 7, no. 2, pp. 170–177, 2004.

[16] R. VanRullen, R. Guyonneau, and S. J. Thorpe, "Spike times make sense," *Trends in neurosciences*, vol. 28, no. 1, pp. 1–4, 2005.

[17] W. Maass, T. Natschläger, and H. Markram, "Real-time computing without stable states: A new framework for neural computation based on perturbations," *Neural computation*, vol. 14, no. 11, pp. 2531–2560, 2002.

[18] J. C. Tapson, G. K. Cohen, S. Afshar, K. M. Stiefel, Y. Buskila, R. M. Wang, T. J. Hamilton, and A. van Schaik, "Synthesis of neural networks for spatio-temporal spike pattern recognition and processing," *Frontiers in neuroscience*, vol. 7, 2013.

[19] M. Kraft, F. Ponulak, and A. Kasinski, "Fpga implementation of resume learning in spiking neural networks," in *Proceedings of EPFL LATSIS Symposium 2006, Dynamical Principles for Neuroscience and Intelligent Biomimetic Devices*. Citeseer, 2006, pp. 97–98.

[20] W. Lee, J. Cabibihan, and N. Thakor, "Bio-mimetic strategies for tactile sensing," in *IEEE Sensors, 2013*. IEEE, 2013, pp. 1–4.

[21] E. M. Izhikevich *et al.*, "Simple model of spiking neurons," *IEEE Transactions on neural networks*, vol. 14, no. 6, pp. 1569–1572, 2003.

[22] J. Wall and J. Crosbie, "Accuracy and reliability of temporal gait measurement," *Gait & Posture*, vol. 4, no. 4, pp. 293–296, 1996.

[23] S. Ghoussayni, C. Stevens, S. Durham, and D. Ewins, "Assessment and validation of a simple automated method for the detection of gait events and intervals," *Gait & Posture*, vol. 20, no. 3, pp. 266–272, 2004.

[24] R. W. Selles, M. A. Formanoy, J. Bussmann, P. J. Janssens, and H. J. Stam, "Automated estimation of initial and terminal contact timing using accelerometers; development and validation in transtibial amputees and controls," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 13, no. 1, pp. 81–88, 2005.

[25] P. Catalfamo, D. Moser, S. Ghoussayni, and D. Ewins, "Detection of gait events using an f-scan in-shoe pressure measurement system," *Gait & posture*, vol. 28, no. 3, pp. 420–426, 2008.

[26] J. Rose and J. G. Gamble, *Human walking*. Lippincott Williams & Wilkins Philadelphia, 2006.

[27] S. Panzeri, N. Brunel, N. K. Logothetis, and C. Kayser, "Sensory neural codes using multiplexed temporal scales," *Trends in neurosciences*, vol. 33, no. 3, pp. 111–120, 2010.