1-D LOCAL BINARY PATTERNS FOR ONSET DETECTION OF MYOELECTRIC SIGNALS

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ABSTRACT

This paper presents a new 1-D LBP (Local Binary Pattern) based technique for onset detection. The algorithm is tested on forearm surface myoelectric signals that occur due to lower arm gestures. Unlike other onset detection algorithms, the method does not require manual threshold setting and fine-tuning, which makes it faster and easier to implement. The only variables are window size, histogram type and the number of histogram bins. It is also not necessary to measure the properties of the signal during a quiescent period before the algorithm can be used. 1-D LBP Onset Detection is compared with single and double threshold methods and is shown to be more robust and accurate.

Index Terms— 1-D Local Binary Patterns, surface electromyography, onset detection

1. INTRODUCTION

Myoelectric signals have been used for control of prosthetic hands since the 1960s [1]. Our work aims to develop a pattern recognition system to make myoelectric upper limb prostheses more useful and intuitive. In this paper, we aim to develop onset detection so that the prosthetic device perceives a user's initiation of a motion. This is realised by detecting when some change in the properties of the signal crosses a threshold. Once onset is recognised, pattern recognition can commence to convert the signal obtained from muscle activation into finger movement commands for the prosthesis.

Onset detection algorithms use parameters calculated from the signal. Methods for onset detection are described in [2] and [3] in which the parameter values are compared against a user-defined threshold or against the characteristics of the signal when no movement is present. The threshold can be adjusted to change the false alarm probability. Double threshold methods such as Bonato [4] also allow control of detection probability. A decision must be made for the value of the thresholds so that the most accurate onset decisions can be made with fewest false onsets.

The Bonato method was designed for gait analysis [4]. It requires whitening of the signal and the manual setting of thresholds. The characteristics of the signal during a quiescent period must also be measured.

Another common onset detection method requires the amplitude of the signal to go above the RMS plus several standard deviations of a quiescent period of the signal [5]. Again, this requires identifying and measuring the characteristics of a quiet period, and the number of standard deviations can be adjusted to alter the sensitivity.

Energy onset simply requires a single threshold to be set; the energy in a windowed portion of the signal must be above the threshold for onset to be declared [2].

The main advantage of 1-D LBP Onset Detection is that there are no manual thresholds: The only variables are the window size, number of histogram bins and the histogram type. In this paper, we propose 1-D Local Binary Patterns with myoelectric signals for onset detection. The principles behind 1-D LBP are described in Section 2. A brief introduction to the myoelectric signal is given in Section 3. In Section 4, onset detection using 1-D LBP is described. Performance is discussed in Section 5. Conclusions are made in Section 6.

2. 1-D LOCAL BINARY PATTERNS

Two-dimensional Local Binary Patterns are commonly used to extract features from images [6]. 1-D LBP is a recent adaptation for one-dimensional signals, in which histograms are generated from data using 1-D LBP codes [7]. The histogram activity is analysed to determine changes in the properties of the signal. In [7], this is used for voice activity detection (VAD) and to separate voiced and unvoiced components. The 1-D LBP is calculated by comparing the neighbouring samples to a sample value $x[n]$:

$$LBP_P\left(x[n]\right) = \sum_{r=0}^{\frac{P}{2}-1}\left\{S\left[x\left[n+r-\frac{P}{2}\right]-x[n]\right]2^r + S\left[x[n+r+1]-x[n]\right]2^{r+\frac{P}{2}}\right\} \quad (1)$$

where $S[.]$ is the Sign function:

$$S[x] = \begin{cases} 1 \text{ for } x \geq 0 \\ 0 \text{ for } x < 0 \end{cases} \quad (2)$$

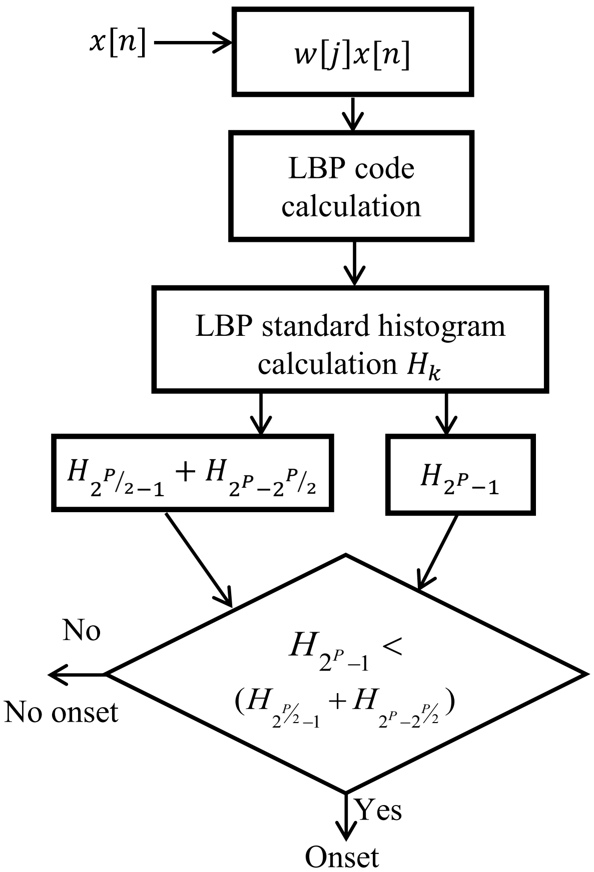


Figure 1 – 1-D LBP Onset Detection algorithm.

There are 2^P possible Local Binary Patterns. From (1), an LBP code is given that reflects the local activity of the signal around the sample value. The distribution of LBP codes within a signal (or within windowed portions of it) is called the LBP histogram [7]:

$$H_b = \sum_{\frac{P}{2} \le n \le N - \frac{P}{2}} \delta\left(LBP_P\left(x[n]\right), b\right) \tag{3}$$

where the signal or windowed portion is of length N, $b = 1..B$, B is the number of histogram bins and each bin corresponds to an LBP code. $\delta(i, j)$ is the Kronecker Delta.

There are histogram variants: Uniform histograms have bins for patterns with at most two 0 to 1 or 1 to 0 transitions, and the other patterns are classed as non-uniform and placed in the same bin. Rotationally Invariant histograms shift the 1s of the LBP codes as far to the left as possible to minimise the numerical value of the LBP code. Uniform Rotationally Invariant histograms take the transition from the last bit to the first into account when determining uniformity [7].

3. THE MYOELECTRIC SIGNAL

The surface myoelectric signal is also known as the surface electromyogram (sEMG). It is a measure of the summed electrical field resulting from the synchronous and asynchronous generation of propagated action potentials initiated in the muscle fibres of contracting motor units in response to neural drive. A single motor unit is composed of many muscle fibres and the summed action potentials of a single motor unit is referred to as a Motor Unit Action Potential (MUAP). The myoelectric signal can be expressed as the sum of attenuated MUAPs with additive noise [8]:

$$x(t) = \sum_j MUAP_j(t) + n(t) \tag{4}$$

$x(t)$ is the myoelectric signal measured at a single surface site, $MUAP_j(t)$ are the j motor units attenuated by tissue and distance. $n(t)$ is additive noise.

3.1 Recording of myoelectric signals

sEMG signals were recorded from three volunteers in the Department of Bioengineering at the University of Strathclyde, UK. All protocols were approved by a local ethics committee. Two dry bipolar electrodes were placed on the intact forearm of the volunteer at sites corresponding to the *extensor digitorum* and the *flexor carpi radialis*. The electrodes have the same form factor as those used in modern myoelectric limbs, with which conducting gel is not used.

Thirty sessions per volunteer were recorded, each of which consisted of five hand gestures held for five seconds with five seconds of rest in between. Four gesture types were recorded in random sequences (tripod, pinch, point and lateral grip). During recording, to control movement onset, the volunteer responded to visual cues displayed on a screen, which provided the name and image of the gesture to adopt (from rest). The timestamps of these cues were logged.

The signals were sampled at 2 kHz. Adjacent windows of size 60ms were used to generate 1-D LBP histograms and for the energy onset method.

4. 1-D LBP FOR MOVEMENT ONSET DETECTION

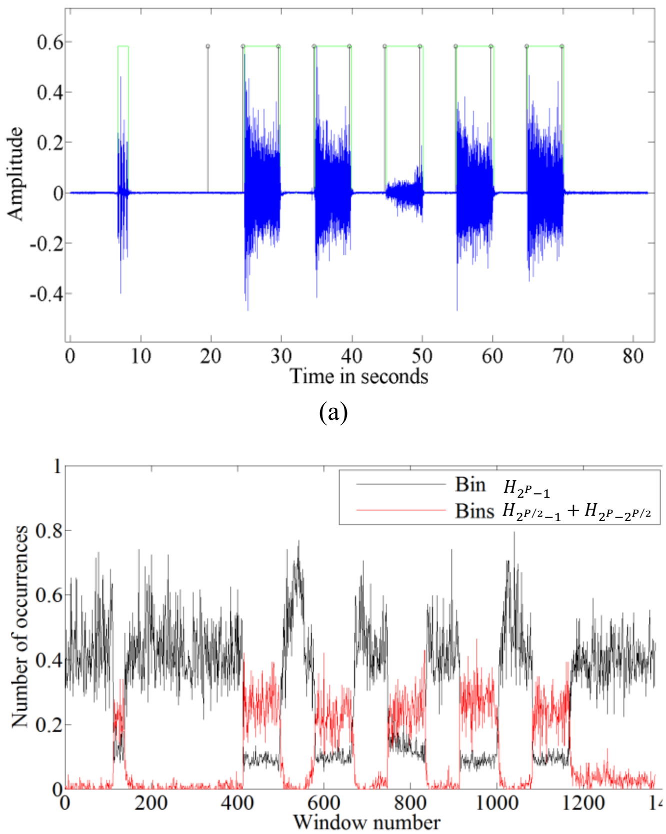
4.1. LBP Onset detection algorithm

For 1-D LBP Onset Detection, it is necessary to measure the difference between histogram bins within successive windows of a 1-D signal. It was observed that the activity in some histogram bins changes greatly based on whether there is muscle activity. Specifically, bin H_{2^P-1} is more active during quiescent periods, and bins $H_{2^{P}/2-1}$ and $H_{2^P-2^{P}/2}$ are more active during muscle movement.

Figure 1 depicts the stages involved in 1-D LBP Onset Detection. For a single channel:

1. The signal is first split up into windows by applying a window $w[j]$ of length W as:

$$x[j] = w[j]x[n] \tag{5}$$



(a)

(b)

Figure 2 – Onset detection based on LBP histogram bin activity (*P=8*). (a) Signal with movement cues and detected activity superimposed (b) Normalised histogram bin activity

2. Calculate 1-D LBP of the windows using (1)
3. Calculate LBP histogram for the windows, H_b as in (3)
4. For each window, sum the contents of the bins that indicate activity $(H_{2^{P/2}-1} + H_{2^P-2^{P/2}})$
5. For each window, determine:

$$S[H_{2^P-1} < (H_{2^{P/2}-1} + H_{2^P-2^{P/2}})]\begin{cases}0 \text{ quiescent period}\\ 1 \text{ muscle activity}\end{cases}$$

   Where *S*[.] is defined in (2)
6. Filter the resulting onset vector such that onset detections with human reaction time of each other are considered part of the same contraction.

Reaction time is an important consideration for onset detection. It is commonly stated that a prosthetic must respond within 300ms or the user perceives sluggishness [9], taking into account that onset, feature extraction and classification must all be calculated within the given time. The time between the movement command and the start of myoelectric activity was measured in our data. This was found to be about 200ms, so this was taken to be the reaction time for the median filter.

5. PERFORMANCE EVALUATION

Figure 2(a) shows a surface EMG signal. The circled markers indicate movement cues. Figure 2(b) shows histogram bin activity (*P*=8) taken from windows of the sEMG signal. During muscle movement, the activity in bin 255 decreases and the activity in bins 15 and 240 increase. The box outline of the sEMG signal shown in Figure 2(a) is the onset detection based on the algorithm given in 4.1.

In Figure 2(b), rapid overlaps in activity can be seen between the two sets of bins during some of the muscle activations; the purpose of the smoothing filter is to address such occurrences.

1-D LBP Onset Detection was compared with other methods, whose parameters were adjusted to give the best possible results for the given data while also minimising false onsets. Figure 3 shows the comparison of 1-D LBP Onset Detection with other methods for one of the sessions. Where windows are used, the window size is 60ms. In Figure 3, the circled lines depict the onset instructions given to the volunteer. Boxes around the signal depict the onset detections. All the parametric methods were fine-tuned to the specific session to get the best possible results.

Figure 3(a) depicts the 1-D LBP Onset Detection, with *P=8,* standard histogram used. The algorithm did not smoothly pick up the entirety of the first two gestures when *P*=8 so *P*=6 and *P*=2 are shown in Figures 3(b) and 3(c) respectively. Changing the value of *P* affects the smoothness of the onset detection. In many circumstances, *P*=2 has the smoothest onset detection even without a smoothing filter.

In Figure 3(d), onset is declared when the signal goes above the Root Mean Square plus two Standard Deviations of the signal measured during a quiescent period. In Figure 3(e), the Bonato method is used, but the signal was not whitened first because it caused an increase in false detections. Threshold was set to $5*10^{-5}$; any higher than this increased false detections (some can already be seen at the end of the gestures). The onset method in Figure 3(f) is energy threshold of 0.002. Energy onset successfully detects all the gestures for their entire duration, but a manual threshold had to be set to achieve this. Setting it higher caused false detections and incorrectly extended the active periods, a lower threshold caused the algorithm to miss more of the valid active periods. In myoelectric forearm prostheses, manual threshold settings are calibrated by a clinician and it is common for patients to return to the clinic for readjustment of threshold values as conditions such as muscle tone and sensor slippage change. This is costly and inconvenient.

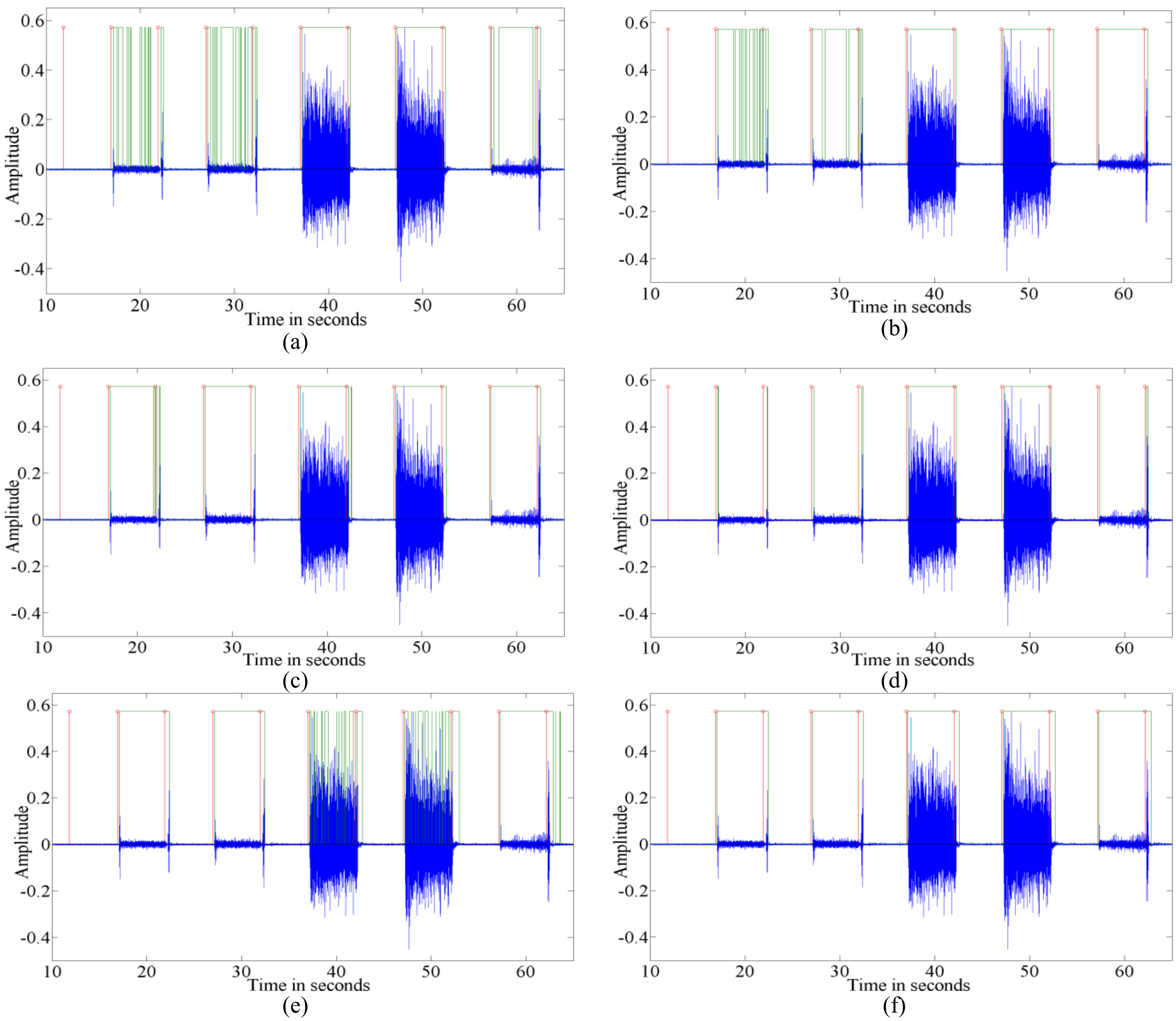


Figure 3 – Comparison of 1-D LBP Onset Detection with other methods, 60ms windows (a) 1-D LBP $P=8$ standard histogram (b) $P=6$ (c) $P=2$ (d) Onset when RMS + 2SD of quiescent, (e) Bonato (unwhitened) threshold $5*10^{-5}$ and 3 consecutive exceeds, (f) Energy onset – threshold 0.002

5.1 Discussion

The resolution of the 1-D LBP onset algorithm is the size of the window, which in this case is 60ms (120 samples at 2 kHz).

It was noticed that the two bins that are active during onset are the same rotated binary pattern (e.g. when $P = 6$, patterns are 000111 and 111000). With this in mind, a Rotationally Invariant histogram was tested. With $P = 6$, onset bins then became H_4 and H_8, offset bin became the last bin, H_{13}.

Two or more sEMG channels are always used in prosthetic limbs. Onset detection must be declared for activity on as few as one channel because most gestures will not activate all the sites at the same time.

A disadvantage of LBP onset (in common with the methods above) is that movement must be initiated from rest and not from during another gesture or different posture. 1-D LBP Onset Detection has not yet been properly tested on recordings of slow, intentional movements.

6. CONCLUSION

In this paper, a new 1-D LBP histogram technique has been demonstrated for onset detection that does not need thresholds and fine-tuning. The only variables are window size, histogram type and the number of histogram bins. In the example given in Figure 3, the value of *P* was adjusted until all the gestures were detected.

The other histogram types (Uniform, Rotationally Invariant and Uniform Rotationally Invariant) can also be used for onset detection because, in common with the standard histogram, certain bins are active during quiescent periods and others are active during muscle activation. This will be investigated in future work.

Other methods are being tested to improve onset detection performance. The performance of 1-D LBP Onset Detection will be tested with added noise. Real time testing of the algorithm is needed.

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