F-VESPA: A Kinematic-based Algorithm for Real-time Heel-strike Detection During Walking

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Abstract— **With over 10 million people currently suffering from significant long-term gait disability in the United States only, robot-assisted rehabilitation and wearable devices are increasingly gaining attention as a mean to regain functional mobility. Since these devices work collaborative and synchronously with the human gait, it is necessary to be able to detect gait events, such as heel-strikes, in real-time. Although many algorithms have been proposed for detecting heel-strikes with either wearable (e.g. Inertial Measurement Units (IMUs)) or non-wearable (e.g. force plates) sensors, there is a great need for employing less obtrusive and reliable sensors that rely only on recording the kinematics of the leg motion. This work proposes a novel and efficient kinematic algorithm, called the Foot VErtical & Sagittal Position Algorithm (F-VESPA), which has several advantages over existing methods. First, it accurately estimates heel-strike events using kinematic data without requiring access to future data points, rendering it the first to our knowledge kinematic algorithm capable of real-time implementation during treadmill walking. Moreover, it does not require tuning of the utilized parameters, rendering it robust to different subjects, conditions and equipment. The algorithm is tested in a large set of subjects across various treadmill speeds, and it is shown to outperform online and offline implementations of existing prominent kinematic algorithms. Using a 150 Hz data collection system, the F-VESPA achieved a total true error of 33 ms (median) in detecting heel-strike. The F-VESPA is the first to our knowledge kinematic algorithm that can detect heel-strike events during treadmill walking in real-time, with high accuracy, robustness and fast response, enabling real-time control of a variety of assistive platforms and devices, among others.**

I. INTRODUCTION

Over 10 million people in the United States currently suffer from significant long-term disability due to stroke, or are living with a lower limb amputation [1, 2]. This population could benefit from robot-assisted rehabilitation and wearable devices, as a mean to regain functional mobility. Since gait support systems need to be synchronized with the human motion [3, 4], precise characterization of the walking phases is critical. Human gait is separated into gait cycles, defined as the intervals between consecutive heel-strikes of the same foot [5]. To ensure proper functionality of the gait support systems, accurate and robust gait segmentation is necessary.

Numerous algorithms have been proposed for the detection of heel-strike events during gait. In general, these algorithms can be divided into two categories based on whether they utilize wearable or non-wearable sensors [6]. In indoor experiments, non-wearable sensors such as force platforms and opto-electronic systems stand out as the most accurate options for gait analysis, with the first representing the gold standard in gait partitioning [6–12]. However, force platforms are not always available or suitable, while they usually require specialized equipment that might complicate the experimental procedure [13, 14]. On the other hand, opto-electronic systems utilize kinematic methods, which represent the most popular technology found in clinical laboratories, and they have been recognized as the gold standard for routine gait analysis [6].

Kinematic algorithms utilize 3D-kinematic data of the lower limbs recorded using a camera motion capture system [15]. After a thorough research we performed in the literature amongst publications comparing and reviewing kinematic algorithms, the Foot-Contact Algorithm (FCA) [12], the Foot-Velocity Algorithm (FVA) [10] and the Foot Vertical Position (FPOSV) method [7] stood out as prominent due to their increased reported accuracy [7, 10–12]. However, most, if not all, kinematic algorithms that have been proposed so far provided only offline estimates for the heel-strike events.

At the same time, applications such as real-time control frameworks for wearable assistive devices [4, 16], functional electrical stimulation and gait biofeedback [8, 17], require the real-time detection of gait phases. For those purposes, wearable sensors, such as accelerometers, foot-switches, gyroscopes, etc., which allow for real-time detection even in outdoor environments [3, 8, 16, 18], have been employed. However, despite the unique portability they offer, wearable sensors present certain drawbacks, such as challenging placement and reduced reliability and durability [9, 15]. Therefore, the question arises of whether a kinematic algorithm could be proposed for real-time implementation that would maintain high accuracy, without being restricted by the limitations of wearable sensors.

In order to address this gap, this work proposes a novel and efficient kinematic algorithm, called the Foot VErtical & Sagittal Position Algorithm (F-VESPA), which has several advantages over existing algorithms. First, the F-VESPA accurately estimates heel-strike events using kinematic data without requiring access to future data points, rendering it the first to our knowledge kinematic algorithm capable of real-time implementation. Moreover, unlike previous works, it does not require tuning of the utilized parameters, rendering it robust to different subjects, conditions and equipment. The algorithm is tested in a large set of subjects across

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various treadmill speeds and it is shown to outperform online and offline implementations of existing prominent kinematic algorithms. The F-VESPA is the first to our knowledge kinematic algorithm that can detect heel-strike events during treadmill walking in real-time, with high accuracy, robustness and fast response, enabling real-time control of a variety of assistive platforms and devices, among others.

II. Methods

A central feature of this paper is the introduction of a new real-time algorithm for heel-strike detection during treadmill walking, followed by its evaluation with real kinematic data and its comparison with real-time and offline implementations of existing algorithms. For evaluation and comparison, we first define the set of kinematic data used throughout the paper in Subsection II-A. Then, the implementation of existing algorithms is discussed in Subsections II-B, II-C and II-D. Since all existing algorithms have been proposed only for offline implementation, specific considerations and changes need to be made in order to be fairly compared with our proposed method. Finally, Subsection II-E details the proposed algorithm.

A. Description of Dataset

In this work, we utilize data from a publicly available dataset [19]. Specifically, in the study by Fukuchi et al., a group of 42 healthy subjects participated, consisting of 24 young adults (age 27.6 ± 4.4 years, height 171.1 ± 10.5 cm, and mass 68.4 ± 12.2 kg) and 18 older adults (age 62.7 ± 8.0 years, height 161.8 ± 9.5 cm, and mass 66.9 ± 10.1 kg). Both kinematic and kinetic data were recorded during treadmill walking at a wide range of gait speeds. Kinematic data were collected at 150 Hz via a camera based motion-capture system (12 cameras, Raptor-4; Motion Analysis Corporation, Santa Rosa, CA, USA), while a dual-belt instrumented treadmill (FIT; Bertec, Columbus, OH, USA) measured the ground-reaction force data at 300 Hz.

The treadmill walking experiments for each subject included trials at eight different controlled speeds: 40%, 55%, 70%, 85%, 100%, 115%, 130%, and 145% of the self-selected speed. The range of the self-selected speeds across subjects was 0.89 - 1.54 m/s.

Lower-extremity kinematics were recorded by tracking the position of 26 anatomical reflective markers. Amongst the available markers, only three were utilized for the implementation of the algorithms analyzed below: the heel (*HEEL*), metatarsal head #1 (*MTH1*) and metatarsal head #5 (*MTH5*) markers[1].

For calculating the ground truth timing of the heel-strike events in the data, we used the force plate measurements to calculate the instance the foot hits the ground, as this represents the gold standard in gait partitioning and heel-strike detection [6–12]. Specifically, the vertical ground reaction force (GRF) component was utilized, after applying a 4^{th} order zero-phase low-pass Butterworth filter with a cutoff frequency of 20 Hz. To match the kinematic sampling frequency, the GRF data were down-sampled to a frequency of 150 Hz. It should be noted that a zero-phase filter was adopted to avoid any temporal delays and hence derive the actual timing of the heel-strike events. According to the literature, typically a threshold level of 5-40 N on the vertical GRF is utilized for the heel-strike detection algorithms [7, 8, 10–14]. We employed a threshold value of 30 N on a rising edge for our dataset.

B. Implementation of the modified FCA

Given the fact that the FCA was rendered as one of the most accurate amongst the kinematic algorithms described in the literature, we believe that it should be used as a reference for the validation of the proposed algorithm. For that reason, presenting the details of its implementation is necessary and is included below.

Due to the nature of the algorithm [12], a real-time implementation is not feasible, and therefore we opted for a modified implementation that includes an offline version with real-time filtering conditions. In detail, the three-dimensional kinematic data were filtered via a 2^{nd} order, low-pass Butterworth filter (cut-off frequency of 20 Hz), without removing any introduced delays from the filter. The FCA detects touchdown using the vertical position of two markers: the posterior midsole of the heel ($HEEL$) and the lateral midsole at MTH5 ($MTH5$). Initially, all prominent local extrema that have a specific prominence and minimum separation were derived. Naturally, this procedure requires the knowledge of the whole signal throughout each trial. In particular, for the local minima, the optimal minimum separation values were derived to maximize the accuracy of the algorithm in each trial, while the same minimum separation was utilized for both markers.

Next, each trial was divided into gait cycles using the prominent local maxima, and for each gait cycle the following procedure was followed. Initially, the timing of the earliest event between the prominent local minima of the two signals is set as the approximate time of touch down (TD_{approx}), while the corresponding marker is selected as the target marker. Based on that, the TI time interval is defined as:

$$TI = [TD_{approx} - o_1, TD_{approx} + o_2], \tag{1}$$

where $o_1 = 6$ samples and $o_2 = 12$ samples. The assigned size of the time interval was decided based on the trials and values noted in [12]. Then, the vertical acceleration of the target marker is derived from its filtered position using finite difference methods. Finally, the time instance of touchdown (or heel-strike) is defined as the most prominent local maximum in the vertical acceleration of the target marker during the time interval TI.

C. Implementation of the modified FVA

Besides the FCA, another algorithm that stood out amongst the proposed algorithms in the literature is the FVA

[1]Pictures of the markers placement can be found here: https://motion-database.humanoids.kit.edu/marker_set/.

[10]. Similarly to the FCA, a modified offline version was implemented for comparison purposes, as described below.

As proposed in [10], the FVA utilizes the vertical position of two markers: the posterior midsole of the heel ($HEEL$) and the metatarsal head II ($MTH2$). In the employed dataset, the $MTH2$ was not available and the metatarsal head I ($MTH1$) marker was used instead. Similarly to the FCA, the kinematic data were filtered via a 2^{nd} order, low-pass Butterworth filter (cut-off frequency of 20 Hz). Next, the midpoint of the $HEEL$ and the $MTH1$ marker locations was computed, as a representation of the foot's center, while its vertical velocity was calculated via finite difference methods. Next, all prominent local minima of the foot's center vertical velocity were extracted by selecting the appropriate prominence and minimum separation. Again, the optimal minimum separation values were calculated to maximize the accuracy of the algorithm in each trial, while a fixed value was selected for the prominence across all trials. Subsequently, in order to distinguish the specific local minima described in [10], constraints were imposed on the corresponding vertical position of the prominent local minima. The constraint imposed was that the foot center should be close to the ground level at heel-strike. Finally, the heel-strike events were defined as the frames that correspond to prominent negative local minima in the foot center's vertical velocity with a corresponding vertical position that satisfies the imposed thresholds.

D. Real-time implementation of the FPOSV

The last algorithm that will be used as a reference is the FPOSV [7]. The FPOSV detects heel-strikes using only the vertical position of the posterior midsole of the heel ($HEEL$). The latter was filtered via a 2^{nd} order, low-pass Butterworth filter (cut-off frequency of 20 Hz), without removing any introduced delays, similarly to the FCA and FVA. In this case, a real-time implementation was possible and hence it was realized.

For each incoming sample, the current vertical velocity is calculated using a first-order finite difference approximation[2]:

$$dy_H(k) \triangleq \Delta y_H(k) = y_H(k) - y_H(k-1), \qquad (2)$$

where $y_H(k)$ is the filtered vertical position and $dy_H(k)$ is the vertical velocity of the heel marker at the sample k, respectively. Next, all future samples are ignored until a local maximum with a temporal prominence of two past and two future samples is found that exceeds a specific threshold (y_{GM}). This criterion is defined in the following equations:

$$dy_H(k) < 0 \; and \; dy_H(k-1) \leq 0, \qquad (3)$$

$$dy_H(k-2) \geq 0 \; and \; dy_H(k-3) \geq 0, \qquad (4)$$

$$y_H(k-2) > y_{GM}. \qquad (5)$$

If all of the above conditions are met, the corresponding sample $(k-2)$ is defined as the "global" maximum k_{GM} for that gait cycle, and a search for local minima is initiated. Then, for each upcoming sample, the vertical velocity is computed again using Eq. (2), and all samples are ignored until a local minimum with a temporal prominence of three past and one future samples is found not exceeding a specific fixed threshold (y_{max}), i.e. meeting the conditions listed below:

$$dy_H(k) \geq 0, \qquad (6)$$

$$dy_H(k-i) \leq 0 \; \forall \; i \in \{1,2,3\}, \qquad (7)$$

$$y_H(k-1) < y_{max}. \qquad (8)$$

A sample $(k-1)$ satisfying these conditions is defined as the heel-strike event for that gait cycle. Moreover, the search for local minima (heel-strikes) is disabled until the next "global" maximum is discovered and the same procedure is repeated until the end of the trial.

E. Proposed Foot VErtical & Sagittal Position Algorithm (F-VESPA)

The proposed algorithm F-VESPA was designed in order to provide a robust and accurate method of detecting heel-strikes in real-time, using solely kinematic data. The algorithm can be considered as a significant extension of the FPOSV algorithm analyzed above, since instead of using only the vertical position, it also utilizes the sagittal position of the heel marker in the subject's leg. Throughout this paper, we will refer the position on the horizontal sagittal axis as the sagittal position. The motivation behind this was the fact that as the leg moves backwards, the rate of change in the sagittal position has a fixed sign, same as the speed of the treadmill belt[3]. As a consequence, this information could be exploited to filter out any unwanted local minima in the vertical position that do not correspond to heel-strikes. It should be noted that this feature is only observed during treadmill walking, hence the algorithm is not suitable for overground walking.

Initially in the implementation, the same real-time filtering conditions were applied, as in the previous algorithms. Similarly to the FPOSV, at the beginning of a trial all incoming samples are ignored until the "global" maximum for that gait cycle is found, as shown in Eqs. (3-5). Then, for each sample k, the current vertical velocity ($dy_H(k)$) is calculated again using Eq. (2), while the sagittal velocity is computed using the following equation:

$$dx_H(k) \triangleq \Delta x_H(k) = x_H(k) - x_H(k-1), \qquad (9)$$

where $x_H(k)$ is the filtered sagittal position and $dx_H(k)$ is the sagittal velocity of the heel marker at sample k, respectively. Next, all future samples are ignored until a local minimum with a temporal prominence of three past and one future samples is found, as shown in Eqs. (6-7). Notice that the fixed threshold shown in Eq. (8) is not necessary in this

[2]Since only the velocity's sign is of interest, the fixed temporal element dt is omitted.

[3]On the used dataset, the rate of change of the sagittal position was negative, but generally, it depends on each dataset formulation of the reference system whether it is going to be negative or positive. That said, the proposed algorithm is based on the fact that the sign is fixed.

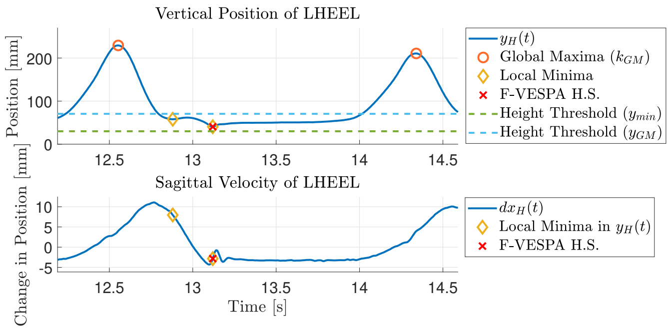

Fig. 1. Example of heel-strike identification using the F-VESPA. Top and bottom subplots show the vertical position and sagittal velocity of the heel marker at a subject's left foot, respectively. Circles (○) indicate "global" maxima and diamonds (◇) indicate prominent local minima in the vertical position. Crosses (×) illustrate heel-strike events identified using the F-VESPA. Heel-strikes are defined as prominent local minima in the vertical position $y_H(t)$ that correspond to a negative sagittal velocity $dx_H(t)$.

case. When such a point is found, the corresponding sign of the sagittal velocity is checked. The point is kept only if the sign is negative, while discarded if positive, i.e. the condition to be met is:

$$dx_H(k-1) < 0. \tag{10}$$

If the condition is satisfied, then the sample $(k-1)$ is defined as the heel-strike event (k_{HS}) for that gait cycle. Based on the vertical position of the heel marker at heel-strike, the y_{GM} threshold is updated:

$$y_{GM} = y_{min} + y_H(k_{HS}), \tag{11}$$

where y_{min} is a fixed variable equal to 30 mm that represents a sufficient height distance between the vertical position of the heel at heel-strike and its next "global" maximum. Moreover, the search for local minima (heel-strikes) is disabled until the next "global" maximum is found and the same procedure is repeated until the end of the trial. The pseudo-code for the proposed F-VESPA algorithm is given in Algorithm 1. Figure 1 demonstrates an example of heel-strike identification using the F-VESPA.

Algorithm 1 F-VESPA

procedure F-VESPA (y_H^r = raw vertical position of heel marker, x_H^r = raw sagittal position of heel marker, f = boolean flag)
  $f = 0$ ▷ Disable search for local minima
  $y_{min} = 30\ mm$ ▷ Define fixed parameter
  while *true* **do** ▷ New motion capture sample
    Obtain $[k, y_H^r(k), x_H^r(k)]$ from motion capture system
    $[y_H(k), x_H(k)] \leftarrow$ Filter (y_H^r, x_H^r)
    Derive $dy_H(k)$ and $dx_H(k)$ ▷ Eqs. (2, 9)
    if $dy_H(k) < 0\ \&\ dy_H(k-1) \leq 0$ **then** ▷ Eq. (3)
      if $dy_H(k-2) \geq 0\ \&\ dy_H(k-3) \geq 0$ **then** ▷ Eq. (4)
        if $y_H(k-2) > y_{GM}$ **then** ▷ Eq. (5)
          $k_{GM} = k-2$ ▷ **"Global" maximum**
          $f = 1$ ▷ Initiate search for local minima
        end if
      end if
    end if
    if $f \neq 0\ \&\ dy_H(k) \geq 0$ **then** ▷ Eq. (6)
      if $dy_H(k-i) \leq 0\ \forall\ i \in \{1,2,3\}$ **then** ▷ Eq. (7)
        if $dx_H(k-1) < 0$ **then** ▷ Eq. (10)
          $k_{HS} = k-1$ ▷ **Heel-stike**
          $y_{GM} = y_{min} + y_H(k_{HS})$ ▷ Eq. (11)
          $f = 0$ ▷ Disable search for local minima
        end if
      end if
    end if
  end while
end procedure

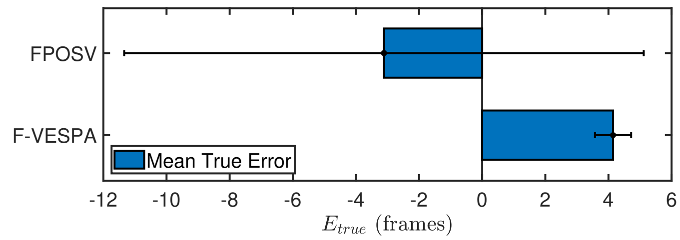

Fig. 2. Evaluation and comparison between FPOSV and F-VESPA algorithms across all trials of young subjects and speeds. Mean values and standard deviations are shown for each algorithm across all trials.

III. Results

In this section, the performance of the FCA (offline), FVA (offline), FPOSV (real-time) and F-VESPA (real-time) in identifying the heel-strike events is evaluated. All algorithms were implemented and executed in MATLAB™ version 9.7 (R2019b) (The MathWorks, Natick, MA USA). The ground truth of the heel-strike event times were determined using the force plate measurements as discussed in Subsection II-A. The accuracy of each method is quantified by defining the estimation error in frames between the real (ground truth) and estimated timing of the heel-strike. For example, if i is the frame at which the heel strike really happened for a gait cycle, and an algorithm estimates the heel-strike at frame $i+3$, then the error for this step is 3 frames. Moreover, if the algorithm estimates the heel-strike earlier than when really occurred (e.g. at frame $i-2$), the error can take negative values, i.e., the error is -2 frames in this example. In order for the comparison to be more generalizable, all the errors are reported in frames, or samples, without imposing a specific sampling frequency for the kinematic data.

A comprehensive evaluation and comparison of the algorithms needs to include multiple subject trials across different walking speeds. Using the aforementioned dataset [19], we evaluated the algorithms using nine young adults that shared similar nominal speeds with statistical significance ($p < 0.05$), across 8 different walking speeds around their nominal speed. Their average nominal speed was equal to $v_m = 1.26 \pm 0.05\ m/s$.

A. Evaluation and comparison between FPOSV & F-VESPA

As mentioned earlier, the F-VESPA is a significantly extended version of the FPOSV that was designed to predict heel-strikes more accurately. Hence, we believe that a comparison between the two is necessary to illustrate their differences and validate the alleged precision. Heel-strike event times were estimated using the two algorithms for all trials. Subsequently, the mean true error (E_{true}) of each algorithm was computed, along with the corresponding standard deviation. The results are shown in Fig. 2 where mean and standard deviation values are shown for each algorithm across all trials. As it is seen, the F-VESPA has a mean error of 4.15 frames and a standard deviation of 0.57 frames, while FPOSV has a mean error of -3.11 frames with a standard deviation of 8.23, while the range of error is from -11.34 to 5.12 frames. This large contrast between

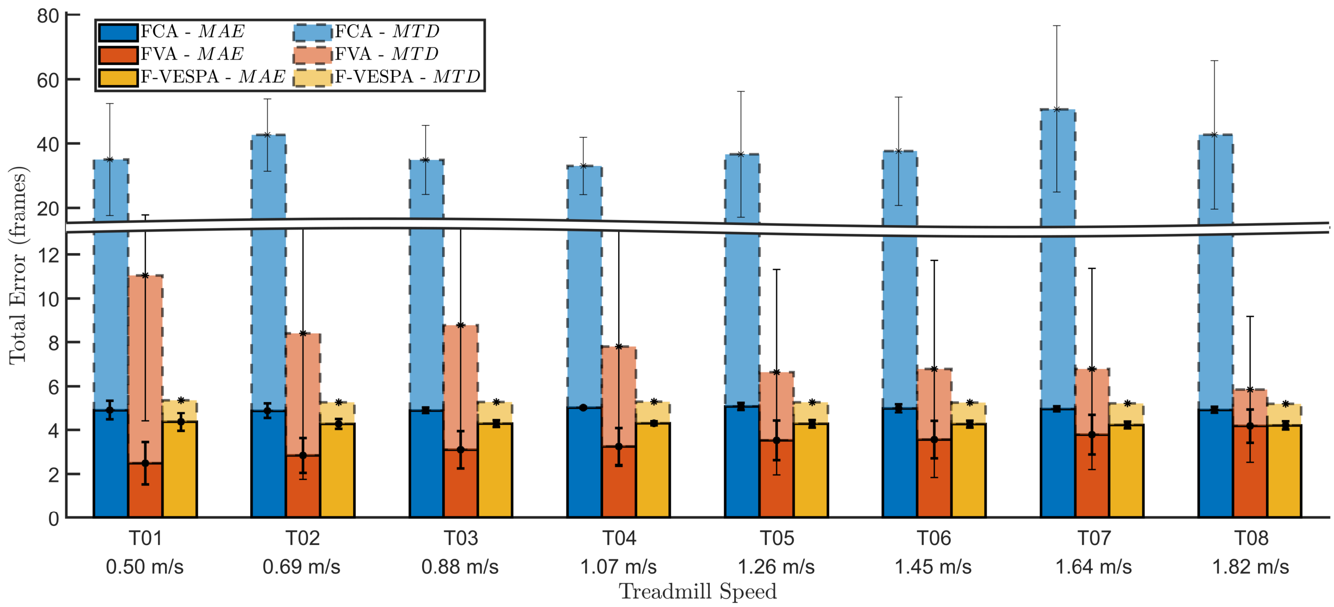

Fig. 3. Evaluation and comparison of the FCA, FVA and F-VESPA algorithms across all treadmill speeds and subjects. Blue, orange and yellow solid bars represent the mean absolute errors (MAE) in frames of the FCA, FVA and F-VESPA algorithms, respectively. Blue, orange and yellow opaque and dashed bars represent the mean time delay (MTD) in frames of the FCA, FVA and F-VESPA algorithms, respectively. The total error is defined as the sum of the MAE and MTD for each speed. Thick black lines represent the standard deviation of the errors across subjects for each speed. Note that the vertical axis was broken into a low (0-12) and a high (20-80) part to emphasize behaviors at different regions.

the two algorithms can be explained by taking into account the main difference between them, which is the inclusion of the negative sagittal velocity criterion shown in Eq. (10). Specifically, given a sample that is the first one to satisfy Eqs. (6-7) after finding a "global" maximum, that condition might lead into the F-VESPA disregarding it. At the same time, if Eq. (5) is satisfied, the FPOSV will classify it as a heel-strike event. In other words, the FPOSV is prone to early detection of heel-strike events, which causes the negative mean error value shown in Fig. 2 with large standard deviation. As a result, the FPOSV provides in many cases erroneous estimations, which lead to a worse performance than this of the F-VESPA.

B. Evaluation and comparison of F-VESPA to FCA & FVA

In addition to the true and absolute errors of estimation, the true time delay required for the calculation of the heel-strike estimation was computed for each algorithm.

Both the FPOSV and the F-VESPA were designed for real-time deployment, while real-time conditions were simulated during their execution. In detail, for a given trial, the algorithms processed each sample one by one, without having access to any future samples. As a consequence, in order to determine whether a given sample has a specific temporal prominence (i.e. Eqs. (3,4,7)), both algorithms had to wait for the required number of future samples. This property introduces an inherent time delay that has to be accounted for when evaluating performance. For both FPOSV and F-VESPA, the inherent delay of their predictions is equal to one sample, as they require a maximum number of one future sample for the identification of heel-strike events using Eqs. (7,8,10).

In contrast, only offline implementations were possible for the FCA and the FVA. Specifically, in both algorithms local extrema were computed with a specific prominence that by definition requires the apriori knowledge of the whole signal. For comparison purposes, only the time delays associated with temporal prominence and time windows are analyzed. For the FCA, knowledge over the whole time interval TI is required as shown in Eq. (1), which introduces a delay of 12 samples. Moreover, local minima required a minimum separation, which was optimized to maximize the performance of the algorithm. Therefore, the time delay for the FCA was defined as the sum of the two components. For the FVA, only the minimum separation for the local minima introduced additional time delay, which was again optimized to maximize the performance of the algorithm.

The results of the FCA, FVA and F-VESPA across all subjects and walking speeds are shown in Fig. 3. For each walking speed, the mean absolute error (MAE) and mean time delay (MTD) are shown, along with standard deviations. The MAE quantifies the accuracy of each algorithm in estimating heel-strike events without taking into account the aforementioned time delays. Then, the MTD needs to be added to each algorithm to show the error in estimating the heel-strike event due to the inherent delay. This is of high importance since we are interested in real-time heel-strike event detection and the MTD captures how late the predictions would be in real-time.

Amongst all implemented algorithms, the F-VESPA exhibits the lowest total error in frames across all speeds and subjects. Although FVA seems to have slightly better performance than the F-VESPA if MAE is only considered across all speeds, its standard deviation is significantly larger than that of F-VESPA. Moreover, the performance of the FVA declined as the treadmill speed increased, while the

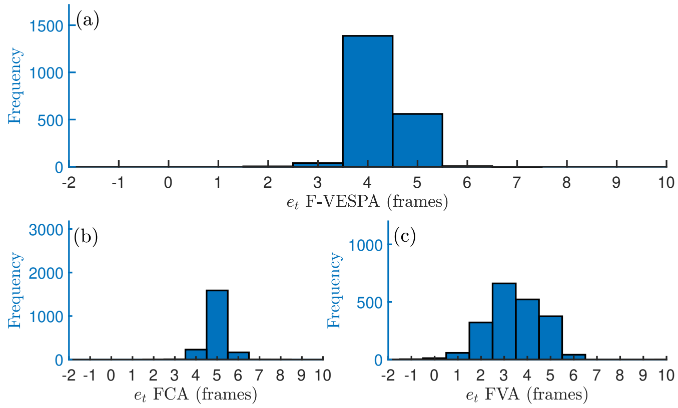

Fig. 4. Histograms of true error e_t in frames for F-VESPA (a), FCA (b), and FVA (c). Bars represent the frequency of each true error value in gait cycles.

performance of the F-VESPA is not affected by walking speed. The error induced due to the inherent time delay of the F-VESPA is equal to one across all trials, hence no deviation is observed. In contrast, both the FCA and FVA have significantly high MTD values, bringing their total error higher than that of the F-VESPA across all speeds.

The statistical differences of accuracy (true error of estimation) between the algorithms were tested using paired t-tests. In both pairs (F-VESPA, FCA) and (F-VESPA, FVA) the null hypothesis was rejected ($p < 0.05$), indicating statistically different distributions of errors among the algorithms.

The distribution of true errors e_t across all trials for each algorithm without including the inherent time delays was calculated for each algorithm, and normal distribution fit was attempted. The histograms of the errors are shown in Fig. 4. The histogram data were tested for normal distribution using the Kolmogorov–Smirnov test [20]. In all three cases, the null hypothesis was rejected using the default significance threshold ($p < 0.05$). Therefore it was determined that the e_t data do not originate from normal distributions for all three algorithms. As a consequence, we choose to compare the data by median and range. Amongst all implemented algorithms, the F-VESPA exhibits the lowest median (4) and range (from 2 to 7) in frames across all trials. The median corresponds to a total error of 5 (4+1) frames or 33 ms (150 Hz sampling frequency). The FCA and the FVA have larger and smaller medians equal to 5 and 3 frames, respectively, while the FCA is more consistent as it has a range from 2 to 8 frames. On the other hand, the FVA has a significantly higher range from -2 to 10 frames.

IV. Conclusion

This paper presents for the first time a real-time algorithm for detecting the heel-strike event during treadmill walking using only kinematic data. The algorithm was shown to have superior efficiency and robustness compared to previous works, even though most of them were implemented offline in much more favorable conditions than the proposed algorithm. As the detection of gait events is important for the implementation of controllers for robot-assisted rehabilitation, wearable and prosthetic devices, the work can significantly advance the field by allowing robust and accurate detection of gait events in real-time using only kinematic data.

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