Decision-tree-based human activity classification algorithm using single-channel foot-mounted gyroscope

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Decision-tree-based human activity classification algorithm using single-channel foot-mounted gyroscope

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Wearable devices that measure and recognise human activity in real time require classification algorithms that are both fast and accurate when implemented on limited hardware. A decision-tree-based method for differentiating between individual walking, running, stair climbing and stair descent strides using a single channel of a foot-mounted gyroscope suitable for implementation on embedded hardware is presented. Temporal features unique to each activity were extracted using an initial subject group ($n = 13$) and a decision-tree-based classification algorithm was developed using the timing information of these features. A second subject group ($n = 10$) completed the same activities to provide data for verification of the system. Results indicate that the classifier was able to correctly match each stride to its activity with >90% accuracy. Running and walking strides in particular matched with >99% accuracy. The outcomes demonstrate that a lightweight yet robust classification system is feasible for implementation on embedded hardware for real-time daily monitoring.

Introduction: The availability of low-cost, low-power microelectromechanical systems technology has led to a recent growth in consumer wearable devices that measure and track daily human activity [1]. The most common commercial devices are typically found on the wrist, upper arm, waist or shoe. Accelerometers have been heavily favoured as the primary sensor in these wearable devices due to their low cost, low power consumption and ability to capture most human movements. However, accelerometers are known to be subject to gravity and the noise introduced by impacts during human movement, which can affect the accuracy or post-processing requirements of the incoming signals. Gyroscopes are resilient to this type of interference, allowing for positioning on lower limbs with less filtering of impact noise and no concern for the changing gravity vector during leg swing. Modern gyroscopes boast a much greater range than traditional devices and are easily capable of measuring the angular velocities produced during general daily activities at high resolution and sampling speeds. Power consumption is still greater than accelerometers, but has reduced to a point where they can be implemented on wearable devices without severely impacting the battery life.

Determining the ideal position to mount sensing devices on the subject is unclear, as placement differs even among publications that are analysing similar movements [2]. This is further compounded by the fact that the majority of papers in this area utilise accelerometers rather than gyroscopes. The practicality of sensor placement also needs to be considered when recording data over significant periods of time, as people will oppose the use of devices that are uncomfortable or unsightly.

Classification algorithms that categorise human activities based on inertial sensing data have been widely investigated [3]; however, results vary greatly and few use gyroscopes as a standalone or primary device. Those that have reported high levels of accuracy (>90%) typically utilise multiple sensor types and require training or intensive processing by external systems [4, 5]. Such methods are unsuitable for implementation on wearable devices due to limited sensing, processing, storage and battery capabilities and therefore require lightweight classification algorithms for real-time application. The use of lightweight methods typically leads to a trade-off in accuracy or variety in recognisable activities. In particular, it has been shown to be difficult when attempting to classify stair traversal with limited hardware, either independently or in conjunction with other activities [6, 7]. What is needed is an alternate method for classifying human activity suitable for implementation on wearable devices. In this Letter, we present a decision-tree-based classification algorithm for recognition of individual walking, running, stair climbing and stair ascent strides using a gyroscopic sensor within a healthy population.

Methodology: The work reported in this Letter consisted of two phases. The first phase was the development of a classification method using data collected from 13 participants. The second phase was to implement the classifier and verify its accuracy using a second group of 10 new participants. Data were collected using a custom inertial sensor unit containing a triaxial gyroscope (±2000°/s) with a sampling rate of 250 Hz. Prior to collection, all participants were assessed to be fit and healthy with no obvious gait impairments and provided consent (Ethics reference ENG/19/12/HREC). One inertial sensor unit was placed on the dorsal aspect of both feet for each participant under the tongue of the shoe or fixed to the laces. The sensors were positioned such that one axis of the gyroscope was closely aligned with the sagittal plane, referred to as the primary channel. Each participant completed a set of exercises consisting of walking (300–400 m), running (100–200 m), stair climbing and stair descent (40–60 stairs each). To maintain real-world representation of typical daily movement, several different walking paths and staircases were used during the collection process and participants were instructed to perform the exercises at self-selected speeds.

Development: Data from only the primary gyroscope channel were imported into MATLAB and filtered using a zero-phase Butterworth lowpass filter (fifth order, $f_c = 4.5$ Hz). Each set of data was split into individual strides using the peak angular velocity during push-off as the endpoints, as it closely aligns with the foot losing contact with the ground [8, 9]. Each stride was then labelled according to its activity type (walk, run, stair up or stair down) for later verification against the classifier decisions.

To allow determination and comparison of the timing of features within the strides, 100 uniformly spaced points were taken between the endpoints to produce a time-normalised sample. Overlaying these samples for all 13 participants in the model development phase (Fig. 1) showed that the overall pattern for a particular activity remained consistent with both intra- and inter-subject regardless of the speed of the stride. Also highlighted were features specific to each activity, such as the timing of the peak velocity of the swing phase (A) and the rotation experienced by the foot during landing at the end of the swing phase (B). From these observations it was hypothesised that by extracting these two features each activity could be uniquely identified using a simple decision-tree-based method.

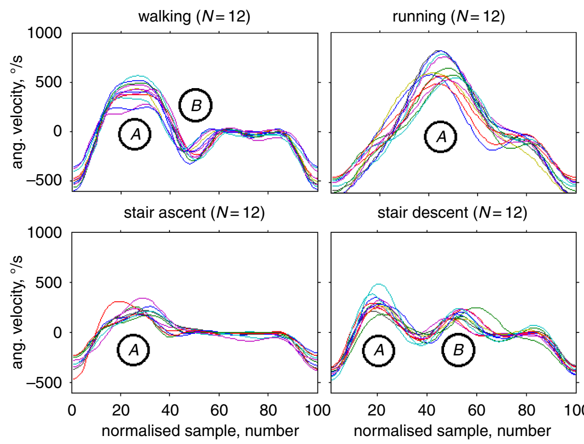

Fig. 1 *Random sampling (n = 12) of time-normalised strides (toe-off to toe-off) overlaid for each activity*

Significant peaks include (A) swing, (B) flexion during landing

For each time-normalised stride across all activities, the position of the peak angular velocity during the swing phase was extracted (A). The position of the secondary peak due to flexion (B) during landing was also extracted for walking and stair descent. Flexion during stair ascent did not generate angular velocities of notable amplitude and running did not show consistent patterns during landing; therefore, secondary peaks were not extracted for these activities. The box plot in Fig. 2 illustrates the spread of these features within each activity, encompassing 99% of the extracted values to remove outliers. Two significant observations were made from these results. First, it was found that swing peaks (A) for running did not overlap with any of the other activities, which allows running strides to be identified based on this feature alone. Secondly, the remaining activities can be distinguished based on the presence and direction of the secondary peak (B).

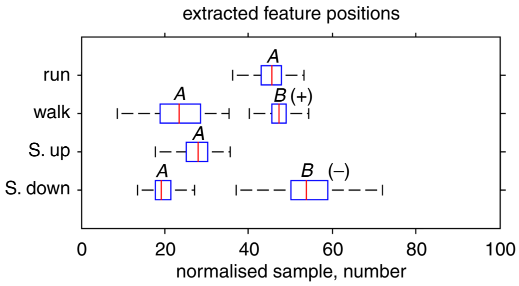

Fig. 2 *Spread of feature peak positions for each activity type*

(*A*) swing peak, (*B*) flexion at landing (sign indicates peak direction). Box boundaries indicate 75% coverage, whiskers extend to 99%

Implementation: Prior to implementation, 10 new participants completed the same set of activities as the initial group to produce new data for verification purposes. Each set of data was tagged according to its activity as earlier for comparison against the final classifier results. A classification algorithm (Fig. 3) was implemented in MATLAB consisting of two stages, with the first stage simply replicating the filtering and extraction process outlined in the development phase to produce a set of individual strides from each dataset. The second stage operated on a stride-by-stride basis, as would be expected for real-time applications, to normalise the number of samples and determine the timings for the swing peak and flexion during landing (if present). Finally, these timings were passed through a decision-tree using the upper and lower boundaries determined previously (Fig. 2) to produce the resultant classification. A classification was deemed correct only if it matched the original activity tag.

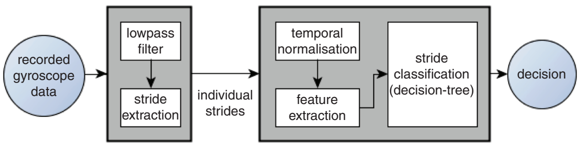

Fig. 3 *Model for stride classification algorithm*

Recorded sessions first separated into individual strides. Each stride classified based on temporal features

Discussion: The results showed a high level of accuracy across all four activities (Table 1). Classification of walking and running activities in particular was shown to be extremely robust with >99% correctly classified. Both stair climbing and stair descent produced lower accuracies in the second test group, and closer examination showed that the majority of errors were produced by two participants. It was found that the extracted features of these participants consistently fell just outside the predetermined boundaries. It is hypothesised that this is due to the variation in individual style during the stair traversal, and that the results would be improved by using a larger sample size to account for this variation. It is also believed that these variations are not as apparent in walking and running due to the more mechanical/movement of these activities.

Table 1: Classifier results for identifying correct activity from single-channel gyroscope data

Phase		Walk	Run	Up	Down
Development	Correct	6582	2637	648	730
	Accuracy (%)	99.3	99.1	94.6	99.6
Verification	Correct	4682	1906	358	496
	Accuracy (%)	99.3	99.2	89.4	92.5
Combined	Correct	11 264	4543	1006	1226
	Accuracy (%)	99.3	99.1	92.7	96.7

Accuracy represents percentage of total strides for that activity

Conclusion: Classification and quantification of daily activity using wearable sensing technology is a growing area of interest, as can be seen through the increasing range of commercial devices. This Letter has presented a lightweight method for extracting and classifying strides into walking, running, stair ascent and stair descent with a high level of accuracy across all activities using a single-axis gyroscope. The techniques used to identify individual strides and extract temporal information are considered to be implementable on embedded hardware for use in real-time applications. Future work will be aimed at incorporating a wider range of activities as well as an expanded number of participants to increase the overall accuracy of the classifier.

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One or more of the Figures in this Letter are available in colour online.

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