Bespoke fuzzy logic design to automate a better understanding of running gait analysis

Fraser Young, *Student Member, IEEE*, Samuel Stuart, Robert McNicol, Rosie Morris, Craig Downs, Martin Coleman and Alan Godfrey, *Senior Member, IEEE*

***Abstract*— Running gait assessment and running shoe recommendation is important for the injury prevention of runners who exhibit different skill-levels and running styles. Traditionally, running gait assessment for shoe recommendation relies upon a combination of trained professionals (e.g., sports-therapists, physiotherapists) and complex equipment such as motion or pressure sensors, often incurring a high-cost to the consumer. Despite this, assessments are still prone to subjectivity, and may differ between assessors. Alternatively, methods to provide low-cost, reproduceable gait assessment has become a necessity, especially within a habitual (low-resource) context, with many traditional methods generally unavailable due to the need of professional assistance and more recently the COVID-19 pandemic. Fuzzy logic has shown to be an effective tool in the assessment and identification of gait by providing the potential for a high-accuracy methodology, while retaining a low computational cost; ideal for applications within embedded systems. Here, we present a novel shoe recommendation fuzzy inference system from the classification of two key running gait parameters, foot strike and pronation from a single foot mounted internet of thing (IoT) enabled wearable inertial measurement unit. The fuzzy approach provides excellent (ICC > 0.9) accuracy, while significantly increasing the resolution of the gait assessment technique, providing a more detailed running gait analysis.**

***Index Terms*— Fuzzy logic, embedded systems, gait assessment, wearable, IMU, running, sports therapy**

I. Introduction

DURING running, an individual's feet and legs are susceptible to impact forces upon ground contact [1]. As the foot makes contact with a surface, a runner will experience some degree of pronation, i.e., the roll of the foot upon impact [2]. Furthermore, runners will exhibit a foot-strike location, measured as the point the foot initially makes contact with the ground during a stride (between heel-strike and fore strike) [3].

Typically, a runner naturally exhibits a unique gait pattern [4] as a result of their biomechanical construction and unique bone architecture [5]. As such, a wide range of injuries can be experienced during participation in running-based activities if the correct running shoe is not worn; most prevalently the likes of Achilles tendon injury [6], plantar fasciitis [7] and shin splints [8]. That can be exacerbated as a result of over-pronation and inadequate running styles. Injuries experienced during running contribute towards significant socio-economic concerns including absence from work and healthcare utilization levels, alluding to a loss of personal income [9, 10].

Support-cushioned assisted running shoes have been shown to reduce strain and minimize damage-potential observed over extensive periods of running exercise [2, 11]. Therefore, it is essential that a suitable running shoe is chosen. In general, running shoes are categorized into pronation assisted and neutral support footwear; with pronation assistance often utilizing cushioning around the heel to reduce roll for over-pronating runners [12]. In turn, understanding these gait features can lead to a reduction in injury risk.

Traditionally, assessment of running gait has several digital approaches but they suffer from lack of availability, high-costs and may only be available in controlled and/or bespoke environments [13, 14]. Techniques exist for real-world/habitual running gait assessment. For example, observing the wear location of well-used running shoes can denote the foot strike location and pronation severity an individual is exerting [15]. Such techniques are highly disputed as runners often exhibit different kinematics when barefoot, compared to when wearing a shoe [16, 17], and results may not be reproduceable, dependent upon the individual performing the assessment. Currently, wearable inertial measurement units (IMU's) are gaining traction as a useful objective means

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F. Young, R. McNicol and A. Godfrey are with the Dept. of Computer and Information Sciences, Northumbria University, Newcastle, UK, NE1 8ST (f.young@northumbria.ac.uk, robert.mcnicol@northumbria.ac.uk, corresponding author: alan.godfrey@northumbria.ac.uk).
C. Downs and M. Coleman are with Mymo Group Ltd, New Century House, Washington, Sunderland, NE39 0AQ, UK (craig@mymo.co.uk, martin@mymo.co.uk).
S. Stuart and R. Morris are with the Dept. of Sport, Exercise and Rehabilitation, Northumbria University, Newcastle, NE1 8ST, UK and Northumbria Healthcare NHS Foundation Trust, UK (sam.stuart@northumbria.ac.uk, rosie.e.morris@northumbria.ac.uk).

to quantify habitual gait activities. Yet, there is a need for real-world inspired analytical methods to provide robust interpretation of IMU data. Here we demonstrate how fuzzy logic can provide robust and more insightful, generalizable running gait assessment, from a low-cost wearable between varying running gait patterns.

II. Background

A. Assessing running gait with an IMU

IMU's have shown to be highly useful in the understanding of an individual's gait through the combination of inertial sensors (accelerometers and/or gyroscopes); providing low-cost, high-resolution, deployable devices to better understand human movement [18]. Accelerating the prevalence of IMU-based gait analysis, their ubiquity and inclusion in wearable devices [19, 20] has seen an increasingly large use in everyday life, cementing the sensor's place in industry and research [21-23].

IMUs have been found to be effective in identifying temporal gait characteristics through identifying phases of gait cycle, denoted by stance and swing times, often located through points of impact and acceleration [24].

B. Fuzzy logic in gait assessment

Fuzzy logic, first introduced by Zadeh [25] denotes a subsection of computing, where rather than Boolean logic (i.e., something is true or false), a degree of membership is given, providing an approximation, rather than an exact.

Fuzzy logic has previously been used to detect and measure gait. Ahamed et al. [26] developed a fuzzy inference system for the detection of speed from runners utilizing a single tri-axial accelerometer. In their work, a simple rule-based fuzzy inference system is deployed based upon the impact severity of acceleration; such that, if acceleration is low then speed is low and conversely with other speeds (medium, fast).

Fuzzy logic has also been shown to address complex gait assessment tasks utilizing embedded wearable devices such as habitual gait event recognition [27]. In the approach, clinically relevant gait phases are identified through a fuzzy inference system. Firstly, fuzzy memberships are defined within a train/test configuration, informing a fuzzy rule set (e.g., a large vertical acceleration may denote a point of contact) to provide a meaningful output of gait characteristics.

Additionally, fuzzy logic has exhibited significant success within embedded domains with IMUs due to the low-computational cost in comparison to approaches such as deep neural networks [28]. In doing so, the maturity of gait assessment with fuzzy logic has extended into a clinically relevant context, utilizing an array of sensors to assess pathological gait [29] and rehabilitation applications [30].

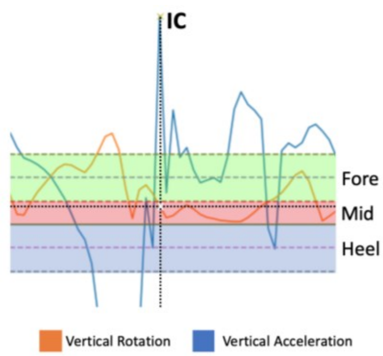

Figure 1 Example of how foot strike location is determined from identification of the foots initial contact (IC) and manual thresholding (fore/mid/heel) of the points around IC within the vertical rotation plane

C. Improving running gait assessment with fuzzy logic

In previous work [31], we presented an application of running gait assessment utilizing a commercial system, an Internet of Things (IoT) foot-mounted wearable IMU. By extracting features through a series of zero-crossing gradient maxima algorithms, the approach informed a neural network to recommend running shoes. In a feature extraction layer approach (Algorithm 1), foot strike and pronation were quantified by manual thresholding, *Figure 1.* A major limitation with the previous methodology was the use of manually selected thresholds for foot strike and pronation, chosen by the visual observation of the distribution of participant data. Especially considering how unique and widely varied gait patterns can be among individuals [32], a fixed threshold-based approach will not necessarily fit all gait types. Additionally, the running gait feature classifications lacked resolution, giving only "Heel", "Mid", "Fore" and "Neutral", "Pronated", "Severely Pronated" for foot strike and pronation, respectively. Those classifications are limited due to the wide variation of contact locations the foot can make during running [3]. Consequently, use of a more flexible and real-world approach is warranted. Particularly, fuzzy logic could enable a 'one size does not fit all' gait assessment approach, utilizing degrees of membership to enable more generalizable outcomes.

Fuzzy logic has also demonstrated utility in understanding signals with extraneous noise [33], of which are particularly prevalent and can be heterogeneous in IMU signals, *Figure 1, Figure 2.* Additionally, fuzzy logic provides a mechanism for reasoning between unclear linguistic variables through assessing the granular output of fuzzy systems [34], effectively increasing the resolution and real-world output of a binary system. This especially applies to the domain of running gait assessment. For example, as a runner strikes the ground, they may 'slightly' pronate in comparison to other runners while exerting a mid/heel strike (i.e., opposed to simply heel striking, they may in fact be subjectively closer to a mid-strike than other heel strikers, warranting a degree of belonging).

Here, we propose a fuzzy inference feature extraction layer to overcome limitations of subjective thresholding for a more nuanced and real-world approach to running assessment, particularly in low-resource settings. The novel design and development of a fuzzy extraction layer aims to increase the resolution and generalizability (and more real-world approach through better interpretation) of running gait assessment. This will provide runners with a better understanding of their running style within an embedded IoT-based IMU.

Algorithm 1 Feature extraction layer [30]

Require: Vertical acceleration plane (AX), horizontal rotational plane (GH), Butterworth filter (polling rate=60Hz, sampling period=3Hz, cut-off frequency=5Hz)

Ensure: Quantify foot strike and pronation of running signal

```
for i=0:length of AX
  if AX[i] is a peak exceeding dynamic threshold
      AX[i] is a point of initial contact (IC), thus
      append AX[i] to list of ICs
for all points of IC
  if IC > 20Hz of last IC
      foot strike location = GH[IC]
      pronation = AX[IC]
```

return average foot strike and pronation experienced for every stride in the signal

III. Methods

A. IMU data collection and labelling

Adult and adolescent runners (*n*=203, 91M:112F) exhibiting a range of abilities (amateur to club runner) were recruited from low-resource, community-based locations within the North East of England. Ethical approval was granted by the Northumbria University Research Ethics Committee (Ref: 21603). Inclusion criteria for participants included the ability to run for 1-minute on a treadmill. No participants reported any condition(s) that would adversely affect their running ability and gave informed consent before conducting a short treadmill-based run.

Participants were fitted with a commercial IoT-based IMU wearable system (www.mymo.co.uk) on the foot, mounting the sensor to the Talus joint, as per the manufacturer's guidelines, *Figure 2*. No participants reported any gait affecting injuries. Participants ran for 2 minutes (1 minute per foot) on a treadmill at a standardized speed of 5mph/8kmph and were video recorded from three angles (front/side/rear) at a frame rate of 240 frames/second (FPS), permitting high-resolution analysis of the runner's gait and manual labelling. During tests, the IMU sensor polls tri-axial accelerometer and tri-axial gyroscope data at 60Hz to a Bluetooth receiver, providing a large dataset of 7200 data points for each inertial axis.

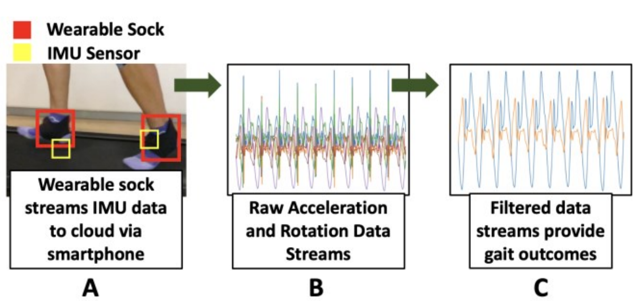

Figure 2 demonstrates (A) Placement of wearable device (talus joint) and IMU configuration with stages of (B) raw data output informing gait outcomes through (C) filtered, cleaned data.

A team of sports-therapists, physiotherapists, and trained researchers manually labelled and cross-validated participants' pronation and foot strike into angular and severity classes such that pronation and foot strike conform to ['Neutral', 'Slight Pronation', 'Pronation' and 'Severe Pronation']; and ['Heel Strike', 'Heel/Mid Strike', 'Mid Strike', 'Mid/Fore Strike' and 'Fore Strike'], providing a ground truth for each respective class, *Figure 3*. In line with common techniques for the measurement of pronation and foot strike [15, 35], multi-angle video data were classified through the observation of angular change of the lower-kinematics surrounding a point-of-impact, *Figure 2*.

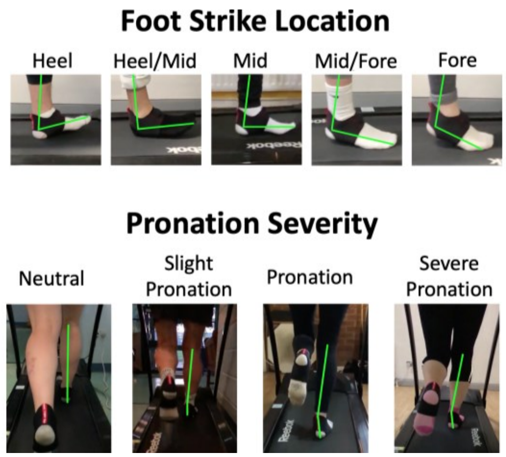

Figure 3 Visual pronation and foot strike labelling method

B. Fuzzy membership design and optimization

It is paramount that optimization of fuzzy membership functions (MF) takes place during the design of a fuzzy system due to how MFs can influence output [36]. Accordingly, an ensemble of fuzzy MFs were benchmarked on the test dataset, including use of (A) *triangular*, (B) *trapezoidal*, (C) *D-sigmoidal* (*D-sig*) and (D) *Pi* membership functions; selected in line with research within the fuzzy logic-based gait assessment domain [37, 38]:

A = triangular membership function

$$mf = \begin{cases} x < \bar{s}, & \nabla[min_s : \bar{s}]x + \ min_s \\ x = \bar{s}, & 1 \\ x > \bar{s}, & \nabla[\bar{s} : max_s]x + \ min_s \\ 0, otherwise & \end{cases}$$

B = trapezoidal function

$$mf = \ max\ (min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0)$$

where a=starting value of class, b = 25th percentile, c=75th percentile, d=maximum value of class

C = D-sig membership function

$$mf = \frac{1}{1 + e^{-a_k(x-c_k)}}$$

comparing two fuzzy sigmoid functions

D = Pi membership function

$$mf = \begin{cases} 0, & x \ \leq a \\ 2\left(\frac{x-a}{b-a}\right)^2, & a \ \leq x \ \leq \ \frac{a+b}{2} \\ 1 - \ 2\left(\frac{x-b}{b-a}\right)^2, & c \leq x \leq \frac{c+d}{2} \\ 1, & b \leq x \leq c \\ 1 - \ 2\left(\frac{x-c}{d-c}\right)^2, & c \leq x \leq \frac{c+d}{2} \\ 2\left(\frac{x-d}{d-c}\right)^2, & \frac{c+d}{2} \leq x \leq d \\ 0, & x \ \geq d \end{cases}$$

where a = starting value climbing from 0, b =25th percentile, c=75th percentile, d = maximum value of class.

The MF characteristics were assigned based upon MF characteristics that are common among similar research [26, 39] in conjunction with preset definitions within Python's *sk-fuzzy* package, utilizing (i) mean (ii) upper/lower quartiles, (iii) minimum/maximum values of the fuzzy sets for MF A, B and D respectively. Visualizations of the observed of MFs and their application within a fuzzy set of pronation severity labels can be seen in *Figure 4.*

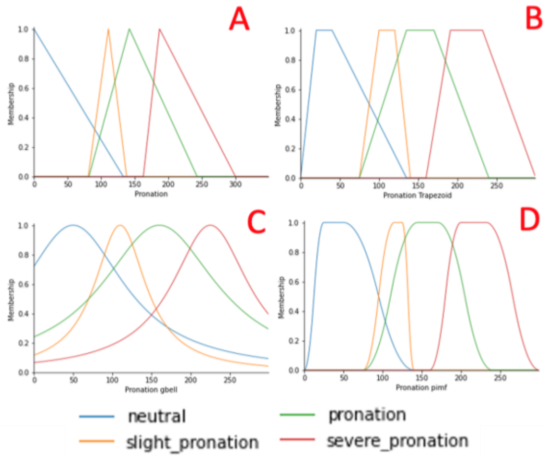

Figure 4 Visualization of membership functions and their corresponding pronation fuzzy sets A – triangular MF, B - trapezoidal MF, C – D-sig MF and D – Pi MF

C. Benchmarking fuzzy designs

Trialing a range of fuzzy designs is paramount to ensure optimal throughput performance between the feature extraction and fuzzy logic system. Membership functions (A, B, C and D) were benchmarked to assess accuracy and execution time of the system design compared with our existing, dynamic thresholding approach. Benchmarks were performed on a cloud instance, with 16GB DDR4 RAM, Nvidia Tesla K80 GPU (4992 CUDA cores, 24GB GDDR5 vRAM) and Intel Xeon (2.2Ghz, 56Mb cache).

D. Fuzzy set design

Similar to previous methodology [31], *Algorithm 1*, foot strike and pronation are quantified through a series of feature extracting, zero-crossing gradient-maxima methodologies to assess the acceleration and rotational inertia of each participants feet, capturing concurrently with their respective video data.

Training and test sets were randomly constructed in a pragmatic 75/25% train/test split ratio in line with studies conducted within similar domains [40, 41]. In doing so, our fuzzy membership system is tested upon 51 runners exhibiting a full range of gait patterns, including foot strike (heel to fore) and pronation (neutral to severely pronated) labels. Using the output of each feature extraction system upon each training data, symmetric triangular fuzzy sets are constructed containing IMU data, segmented by each corresponding gait feature, foot strike and pronation.

E. Raw data to fuzzy interpretation

The flow of creating a fuzzy set is shown in *Figure 5.* The IMU sensor streams 1-minute of accelerometer and gyroscope data to a smartphone application. Data is then transferred to a feature extraction layer:

1) Extraneous noise within the inertial signal is filtered using a Butterworth filter, configured at 60Hz with a sampling period of 3Hz and a cut-off frequency of 5Hz
2) Strides within the inertial signal are segmented using zero-crossing gradient maxima informed dynamic signal segmentation method, such that:

$$(IC_p < IC_{p+1} - \frac{\bar{x}}{2} \rightarrow IC_{p,valid})$$

   where IC denotes a potential point of impact with the ground (initial contact), identified through a gradient change, and $\bar{x}$ is the average stride length of the runner. In doing this, we ensure false positives are ignored for identification of strides within the signal.
3) Pronation is calculated as the severity of roll within the longitudinal rotation axis (value between 0 – 300).
4) Foot strike is calculated as the angle of the foot during impact, quantified by observing the vertical rotation during IC (value between -400 – 100) [31].

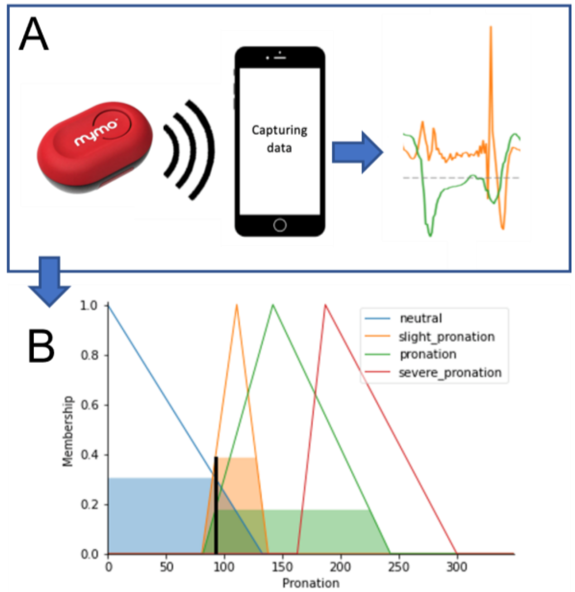

Figure 5 Flow of creating a fuzzy set from A: IMU data stream to phone and feature extraction from raw data to B: fuzzy set construction.

The output of the feature extraction layers are then added to a triangular membership function, corresponding with their label, visualized in *Figure 6*.

F. Fuzzy membership inference throughput

With fuzzy sets defined in accordance with training data labels, running gait fuzzy membership inference is similar to previous work [31]. Previously, the IMU-based wearable streams data to a smartphone where feature extraction occurs through zero-crossing gradient maxima algorithms, returning pronation and foot strike. Here, throughput of features is fed to a fuzzy membership inference system, where degree of membership of foot strike and pronation is calculated *Algorithm 2*.

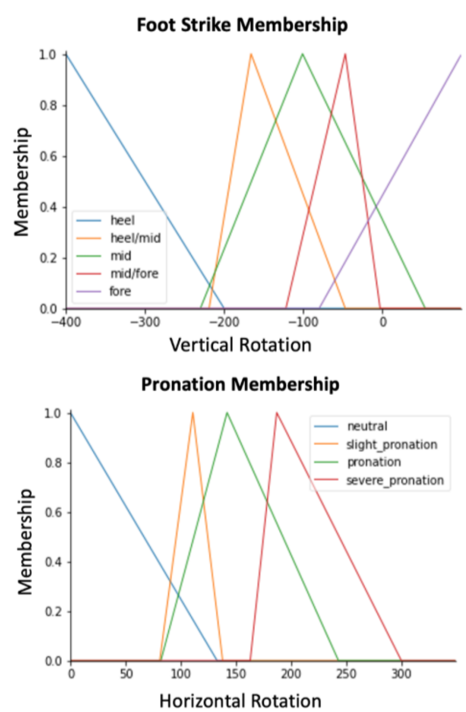

Figure 6 Fuzzy memberships for foot strike and pronation, constructed from 203 participants

Algorithm 2 Fuzzy inference throughput using triangular membership function

Input: Gait feature, *GF*, value from feature extraction layer (either pronation or foot strike)

Output: Gait feature degree of membership for each fuzzy set, *DoM*

```
1: for each membership class, M, within the fuzzy set
2:    if GF not in bounds M
3:        DoM = 0
4:        end
5:    DoM = M[GF]
```

return set containing degree of membership (*DoM)* for each fuzzy set

G. Data analysis

Test data underwent statistical analysis as outlined previously [31], where membership function optimization was examined to the existing IoT IMU system utilizing intraclass correlation coefficients (ICC's) and Pearson's correlation to compare results between methods and optimize the performance of the new fuzzy approach. Equally, ICC's and Pearson's were used to examine the efficiency of the novel fuzzy inference compared to the previous dynamic threshold approach for benchmarked. Analysis were performed for left and right feet based upon pronation and foot strike pattern of each.

In performing analysis, we provide a metric for comparison between our fuzzy approach and existing work utilizing dynamic thresholds. Shapiro-Wilk tests were conducted upon our dataset, with a significant output ($p > 0.087$) indicating a normal distribution of data; therefore, validation of the proposed system implemented $ICC_{2,1}$ and Pearson's correlation coefficients for parametric testing. Use of $ICC_{2,1}$, provides a reliability index for test-retest, intra-rater and inter-rater reliability analytics [42], providing an assessment of system performance between raters, i.e., manual labels and fuzzy logic output.

A 10-fold cross validation data split has been applied to explore the performance of the approach with minimal bias. Through conducting a 10-fold cross validation, we can ensure that outputs are more representative and reproduceable across wider and varied datasets [43, 44]. This notion is fundamental for use in an accurate commercial product due to the potential of widespread use by the general public that could exhibit a highly varied and unique gait pattern [4]. Additionally, analysis of the resulting tests were conducted through observation of confusion matrices, standard deviation and variance to ensure a robust assessment of performance. In line with ICC performance defined by Koo & Li [42], accuracy can be defined such that it satisfies either a poor (< 0.5), moderate (0.5-0.75), good (0.75-0.9), or excellent (>0.9) accuracy.

IV. Results

A. Fuzzy optimization

Through the use of a triangular membership function within the fuzzy system design, we experience optimal accuracy in both $ICC_{(2,1)}$ and Pearson's correlation tests, with comparatively low execution times (within 0.03s of fastest execution), *Table 1*.

Table 1 Results of fuzzy optimization experiment

Membership function	***$ICC_{(2,1)}$***	***p***	***ExT(s)***
A - Triangular	**0.923**	**0.915**	**0.081**
B - Trapezoidal	0.911	0.913	0.080
C - D-Sig	0.834	0.829	0.083
D - Pi-MF	0.912	0.910	0.078

MF = Membership functions.
ExT = Execution times measured for entire throughput of system

B. Fuzzy performance

Results were collected through the application of the fuzzy membership inference system upon the test dataset containing 51 runners, of which no dropout or invalid results were obtained. Each participant provided 1 minute of running per foot, with each foot producing a unique foot strike and pronation, granting a total test dataset size of 204 features.

Analyzing the output of our fuzzy membership inference system (Table 2B) in comparison to manual labelling and previous algorithmic approach (Table 2A) demonstrated excellent accuracy, with $ICC_{2,1}$, ranging from 0.916 to 0.933. Pearson's correlation coefficient was calculated as a reliability measure, and report equally high performances, ranging from 0.892 to 0.933. Confusion matrices visualizing the accuracy can be seen in *Figure 7.* Time benchmarks are measured to assess the execution time between the original threshold-based gait feature classifier and the proposed fuzzy logic system. As shown, inclusion of a fuzzy logic gait feature assessment performs on average 0.01s slower (~12.7%), across an average system throughput, *Table 1*. Crucially, the presented fuzzy logic approach to running gait assessment performs near-equally to the manual thresholding approach, but with a significantly higher gait assessment resolution (i.e., specific pronation severities including slight and severe pronation).

Table 2 Results of original and fuzzy approach compared with the manual labelling reference and general execution times.

Manual thresholding approach (A)						
	Left Foot			**Right Foot**		
Feature	*ICC$_{2,1}$*	*p*	*ExT (s)*	*ICC$_{2,1}$*	*p*	*ExT (s)*
Pronation	0.941	0.938	0.068	0.929	0.915	0.071
F. Strike	0.919	0.927	0.074	0.938	0.937	0.070
Fuzzy logic approach (B)						
	Left Foot			**Right Foot**		
Feature	*ICC$_{2,1}$*	*p*	*ExT (s)*	*ICC$_{2,1}$*	*p*	*ExT (s)*
Pronation	0.916	0.918	0.078	0.924	0.892	0.082
F. Strike	0.919	0.915	0.085	0.933	0.933	0.079

ExT = Execution times measured for entire throughput of system with original/fuzzy classification layers interchanged.
F. Strike = Foot strike.

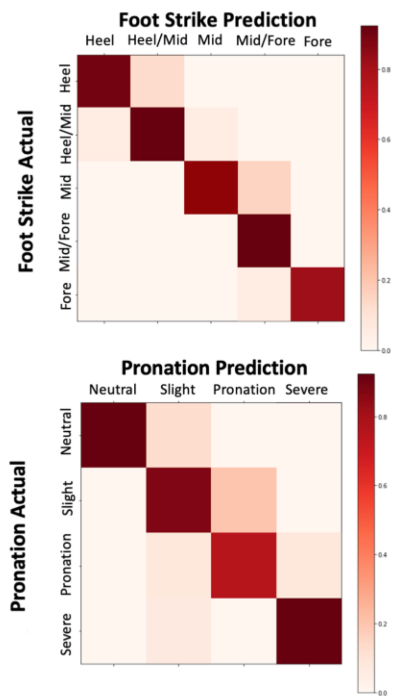

Figure 7 Performance of the fuzzy system classifying foot strike and pronation

C. 10-fold cross validation

Train and test data were randomly split and benchmarked ten times to assess the reliability of the proposed system in a more-generalizable cohort, *Table 3*.

Table 3 10-fold cross validation results obtained through randomly splitting train and test sets 10 times to minimize data bias

Gait Feature	***ICC$_{(2,1)}$***	***p***
Pronation	**0.897**	**0.836**
Foot Strike	0.919	0.877

The approach performs well under a 10-fold cross validation, demonstrating good (0.75 – 0.9) and excellent (> 0.9) intraclass correlation scores for pronation and foot strike respectively between ground truth and the fuzzy logic approach. Furthermore, Pearson's correlation coefficient shows good reliability for the approach with respect to ground truth data ($p \geq 0.836$).

V. Discussion

The presented work utilizes novel fuzzy sets constructed by a large cohort of runners to provide an accurate degree of membership for foot strike and pronation, useful real-world gait features for objective running gait assessment. Our optimal fuzzy results cohere to an excellent standard defined by Koo & Li (ICC > 0.9), with little variance from the expected results, demonstrated by Pearson's correlation and visual assessment of confusion matrices, *Table 2*. Additionally, through performing a 10-fold cross validation data split, *Table 3*, the fuzzy approach demonstrates robustness in a varied testing cohort ($ICC_{(2,1)} \geq 0.897$; $p \geq 0.836$). To the authors knowledge the fuzzy method proposed here is developed on the largest cohort in the field of running gait assessment (n>200), which provides a suitably heterogeneous dataset due to the variation in raw gait signals. In comparison, previous studies have utilized smaller cohorts which may negatively impact generalizability [26, 39,40],

Our novel approach utilizing fuzzy logic is comparable with studies within running and walking gait assessment domains [26, 39, 45], while using a low-cost, single wearable device. Through the application of fuzzy gait assessment with the IoT device, a single, foot-mounted wearable IMU; runners, sports-therapists and related parties can remove over-reliance upon expensive equipment such as high-speed cameras [46], 3D-motion capture [47] and pressure sensitive technologies [48]. Additionally, it removes the previous subjective approaches of manual thresholding [31], consequently, the use of fuzzy logic can provide a more generalizable, dynamic gait assessment that can be flexibly applied to a range of running styles and abilities.

In performing the proposed work, the use of the inertial device and fuzzy approach limits the requirement of professional supervision for operation (i) reducing high-cost and barrier of entry associated with running gait assessment while (ii) providing pragmatic and improved running gait feature classification [20]. Furthermore, this was achieved in a low-resource (community-based) setting which demonstrates the pragmatic implication of accurate running analysis with a low-cost, IoT enabled wearable with a fuzzy analysis. Indeed, the implications of COVID-19 have extended to gait assessment, often inhibiting in-store (or in lab) analysis, prompting the need for research into the application of habitual gait assessment [49]. As such, through using an IoT enabled device with fuzzy logic, we can contribute towards the need for such methods.

Previous work [31] was limited by relying upon manual observation to implement subjective and fixed thresholds for the degree of pronation and foot strike location. Although useful, the approach could quantify if a runner was a neutral or pronated, as well as a heel/mid/fore striker. However, the approach was limited in many ways. Firstly, the approach lacked resolution. For example, although the previous method could correctly classify a runner as a mid-foot striker; it gave no insight to the accurate location of impact (i.e., they may initially strike heel/mid or mid/fore). Secondly, gait assessment of pronation and foot strike is highly subjective between runners and raters alike [50]. As such, use of a fixed-threshold based approach is not necessarily indicative of the wider running population due to the wide variation and subjectivity of running styles or within runner variation due to subtle changes in running environment or between strides [51]. For example, runners may exhibit a varied foot strike angle upon every stride beyond the tolerance of a fixed threshold, Figure 8.

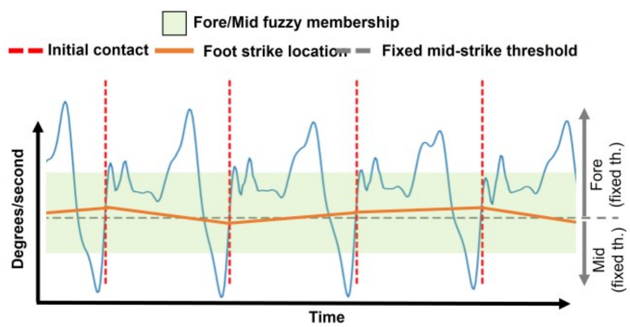

Figure 8 Illustration of slight variance of where initial contact may occur between strides. In real world data capture, the foot strike location may slightly deviate above or below a subjective fixed "mid" strike threshold from stride to stride. Use of fuzzy degree of memberships better understands the degree of belonging (e.g., fore/mid strike). Th = threshold.

Critically, by providing a fuzzy set of gait features, the resolution of IMU-based running gait assessment is drastically increased, and we can more accurately quantify the degree of membership of foot strike and pronation a runner may exhibit, thus, providing a more dynamic, generalizable assessment based upon real data. In comparison to the statistical output of previous work, as shown in *Table 2,* our approach utilizing fuzzy inference performs within a 4% margin of error while providing a significantly higher resolution gait assessment tool.

Fuzzy logic is highly suitable in embedded systems due to its low computational complexity and ability to perform potentially complex computations [52, 53]. *Table 1,* illustrates that executions took place within ±0.01s of the original threshold based approach, pertaining an extremely light computational load. In line with previous work [28], the light computational load experienced during execution of running gait assessment with fuzzy logic ensures the approaches suitability of use within an embedded IMU application.

VI. LIMITATIONS AND FUTURE WORK

During data capture, amateur and club runners were asked to run at a standardized pace of 5mph/8kmph for a period of 1 minute per foot. It should be noted, however, that running styles are susceptible to change with respect to speed and contact forces [54-56]. As such, further validation of running cohorts exhibiting a varied range of speed, abilities and running styles is required to ensure the accurate quantification of foot strike and pronation to accurately inform a running gait assessment.

Optimization of the system required implementation of Python's scikit-fuzzy toolkit. Unfortunately, the framework does not include the full variety of membership functions for testing. Further work is required to include a wider range of fuzzy membership functions to ensure the most optimal performance setting which may have use in high performance running.

As discussed, there are running features other than pronation and foot strike that can be relevant within a running performance and rehabilitation context. Therefore, considering the accuracy of the presented system, further testing will be conducted to increase the feature-count a fuzzy system can provide to further optimize the IMU-based running tool.

Video data capture sessions took place in low-resource settings with varied lighting conditions. Although the approach enabled the relatively low-cost, low-resource development of a habitual running gait assessment tool, some video data sessions lacked clarity; and as such may not exhibit true accuracy. In resolve, future data capture sessions require extraneous lighting apparatus to ensure an accurate assessment.

VII. CONCLUSION

Here, we have developed a novel fuzzy logic application for the classification of key parameters within running gait assessment (for recommended shoe type). The presented method provides a more real-world assessment of running gait, as captured in a low-resource setting with an IoT enabled wearable. In doing so, runners are provided with a (near real time and) significantly higher resolution gait feature fuzzy extraction layer (pronation and foot strike), with a mean average error within 4% of previous work utilizing manual thresholds with lower resolution. Through the use of fuzzy inference, the IoT IMU-based tool performance as an embedded system is largely unaffected, with similar execution times for the throughput of the entire system within 12.7% of previous methods. Future work will extend the current fuzzy approach to enable the assessment of a wider variety of useful running gait assessment metrics such as cadence, contact time and vertical impact.

VIII. REFERENCES

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