Optimal Feature Extraction and Feature Subsets for Various Machine Learning Algorithms Targeting Freezing of Gait Detection

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Okinawa, Japan

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Overview

1. Background
2. Feature Extraction
3. Feature Selection
4. Conclusion

Background

Freezing of gait and the research behind it.

Freezing of Gait

- Irregular gait pattern associated with Parkinson's disease

An episodic inability lasting seconds to generate effective stepping

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- Mostly observed during turns, gait initiation, passing narrow spaces, stressful situations, reaching destination

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An episodic inability lasting seconds to generate effective stepping

- Roughly 50% prevalence among PD patients
- Mostly observed during turns, gait initiation, passing narrow spaces, stressful situations, reaching destination
- Freezing of gait is associated with **falls**
  - 20-30% of falls lead to mild/severe injuries
  - 1900 hospital visits in Singapore per year (age>60)
  - Can be expected to grow due to demographic shift

Research Objective

Objective:

- Provide warnings and aid in overcoming FoG by a wearable system

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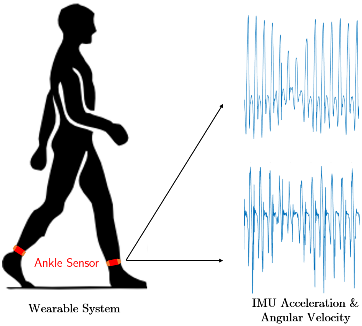

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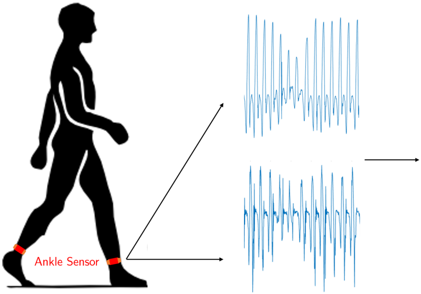
- Extract features that correlate well with the occurrence of FoG



Wearable System

IMU Acceleration & Angular Velocity

Feature Type	Prevalence
Frequency Domain	**63.83%**
1. freeze index (FI)	27.66%
2. freeze band (FB)	2.13%
3. locomotor band (LB)	2.13%
4. mean frequency (mean f)	2.13%
5. dominant frequency (dom f)	4.26%
6. power	17.02%
7. spectral entropy (entropy)	8.51%
Raw IMU Data	**21.28%**
1. root mean square (rms)	4.26%
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Features for Classification

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Detection Systems:

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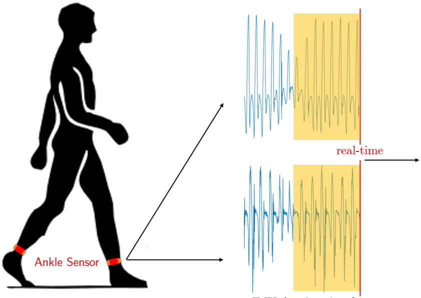
- Extract features that correlate well with the occurrence of FoG
- Extraction must be in real-time



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Features for Classification

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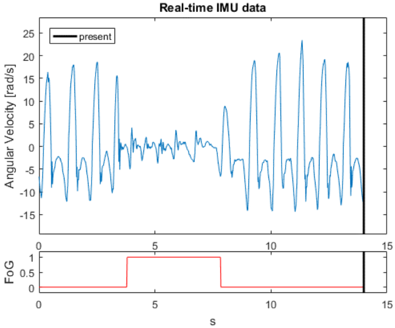

- What is a good data window length?

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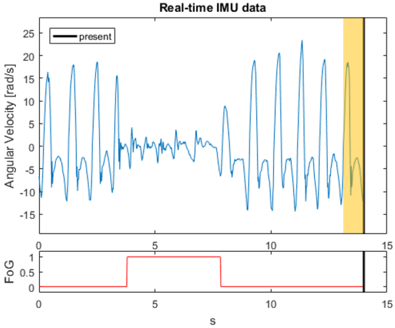

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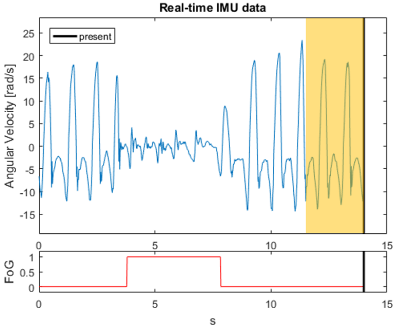

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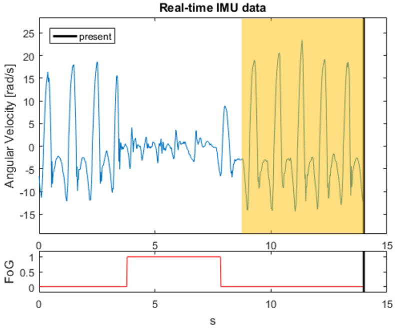

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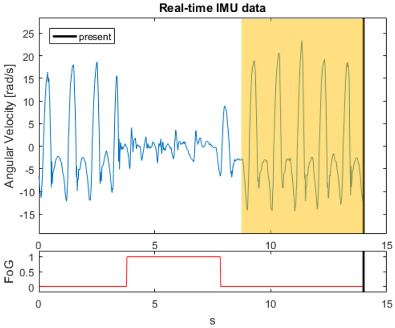

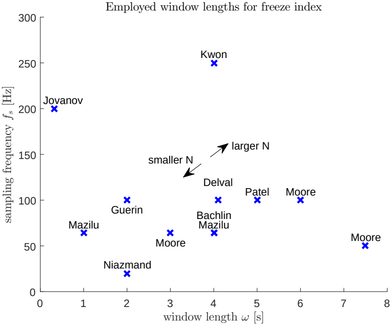

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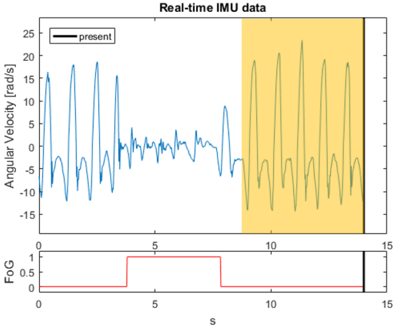

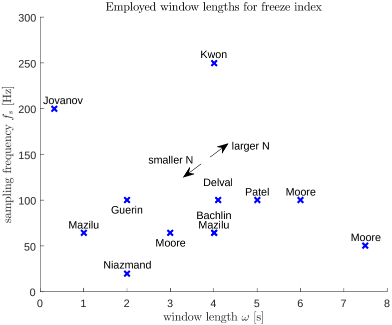

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- Discrepancy in literature
- Does it matter?

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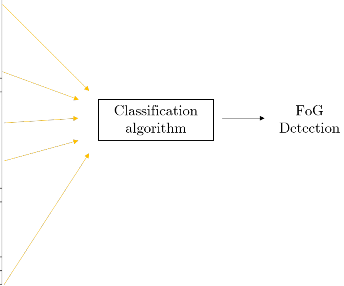

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$\boxed{\text{Classification algorithm}} \longrightarrow$ FoG Detection

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Classification algorithm → FoG Detection

- What is a good feature subset?
- No thorough analysis on feature selection for FoG available

Purpose of This Work

1. **Feature Extraction:**
    - What are the optimum window lengths?
    - Does the window length affect classification performance?

2. **Feature Selection:**
    - Given all published IMU features for FOG detection, what are good subset thereof?
    - How do these compare against previously published feature sets?

Feature Extraction

Optimal window lengths for feature extraction and their significance.

Evaluation Metric

- How much does knowledge about the extracted feature tell us about the class we are trying to predict?

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Mutual information

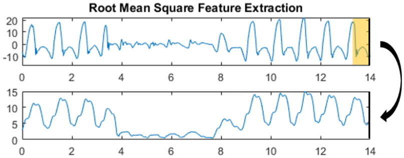
$$I(X,Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \cdot log_2 \left(\frac{p(x,y)}{p(x) \cdot p(y)} \right)$$

- Given feature F extracted with window length ω and the FoG class, find ω which
$$\max_{\omega} I(F(\omega), FoG)$$
- worst case: $I(F(\omega), FoG) = 0$, $F(\omega)$ and FoG independent
- best case: $I(F(\omega), FoG) = 1$ bit

Optimal Window Lengths – Root Mean Square

- Extract feature at various window lengths

Optimal Window Lengths – Root Mean Square



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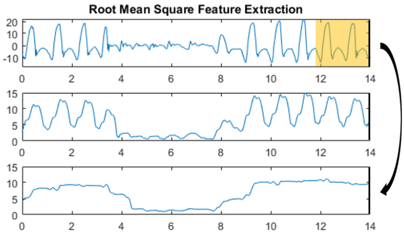

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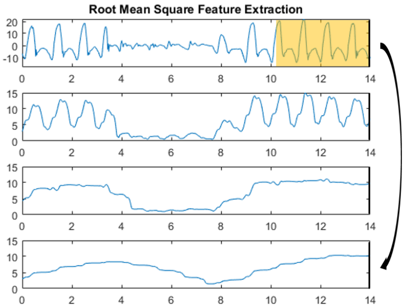

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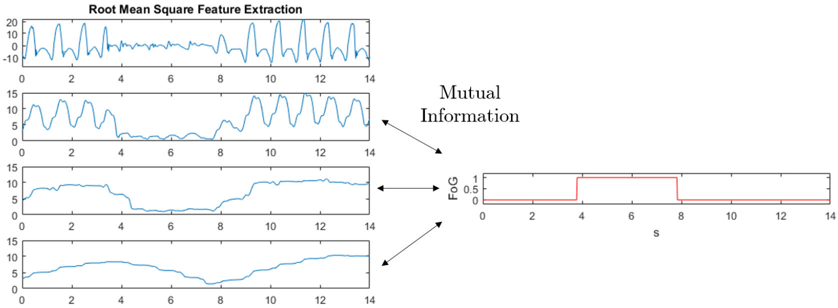
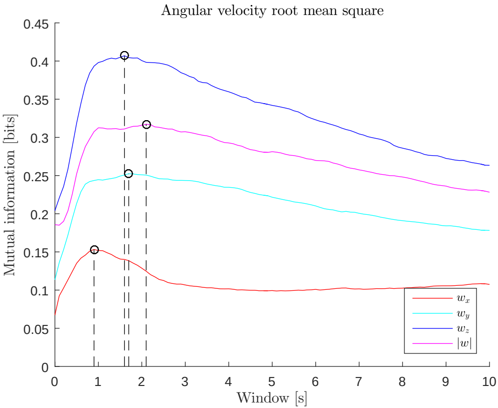


- Extract feature at various window lengths
- Compute mutual information as evaluation metric

Optimal Window Lengths



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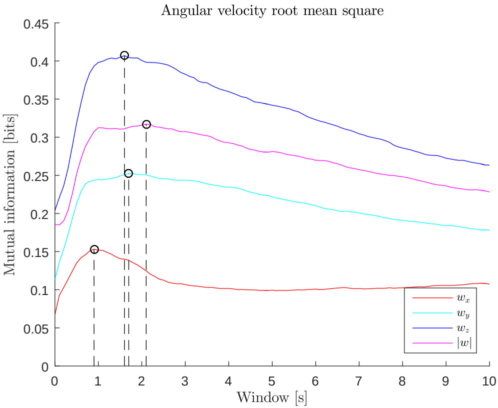

- Angular Velocity RMS
  $\rightarrow \omega_{opt,x} = 0.9s$
  $\rightarrow \omega_{opt,y} = 1.8s$
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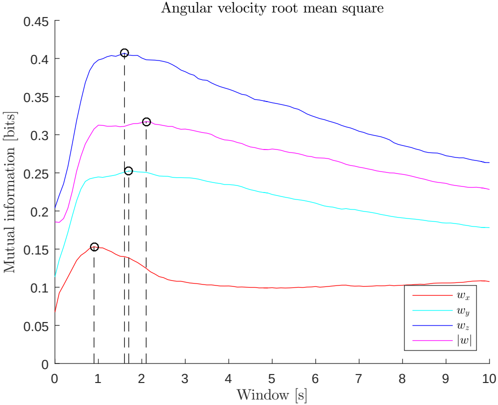

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- **Optimal window lengths** of 117 features in paper.

Significance – Window Length

- Answering the question: Does it matter?

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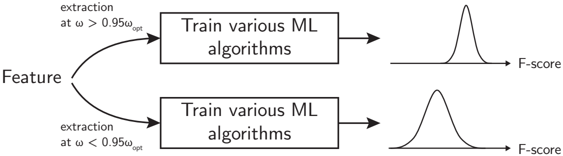


- One-tailed independent t-test

Null hypothesis

$$H_0 : f(F_{opt}) \leq f(F_{n-opt})$$

Alternative hypothesis

$$H_1 : f(F_{opt}) > f(F_{n-opt})$$

Significance

Feature type	Feature axis	$I(F, FoG)$	Window ω_{opt}	Window $\mathcal{W}$	Performance $\mu_{f_1(F_{opt})}$	Performance $\mu_{f_1(F_{n-opt})}$	Performance $\Delta\mu_{f_1}$	Significance p_{window}	Significance p_{signal}
rms	w_x	0.1539	0.9 s	[0.7, 1.4] s	0.7670	0.7439	0.0231	$p < 0.001$	$p < 0.001$
	w_y	0.2553	1.8 s	[0.7, 3.6] s	0.7581	0.7354	0.0227	$p < 0.01$	
	w_z	0.4078	1.6 s	[0.8, 2.9] s	0.8621	0.7946	0.0675	$p < 0.001$	
	$\|w\|$	0.3182	2.1 s	[0.8, 3.6] s	0.8409	0.7780	0.0629	$p < 0.001$	

- Alternative Hypothesis (window)

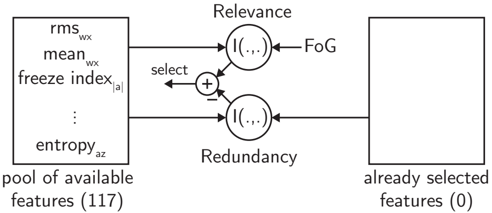
$$H_1 : f(F_{opt}) > f(F_{n-opt})$$

- Results of 117 features in paper
- Window length **predominantly significant**

Feature Selection

Optimal feature subsets for various machine learning algorithms.

Maximum Relevance Minimum Redundancy



- 117 features, $\approx 10^{35}$ feature subset possibilities

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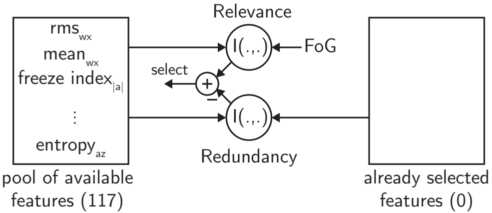

- 117 features, $\approx 10^{35}$ feature subset possibilities
- Select the feature F which $\max_F \Phi = \alpha - \epsilon$

Relevance: $\alpha = I(F, FoG)$ **Redundancy**: $\epsilon = \frac{1}{n}\sum_{i=1}^{n} I(F, F_i)$

where $F_i, i \in [0, n]$ are already selected features

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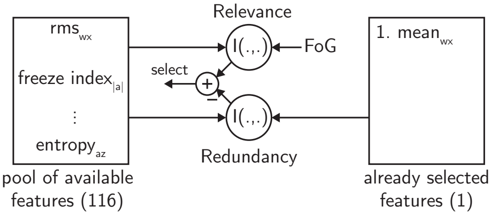

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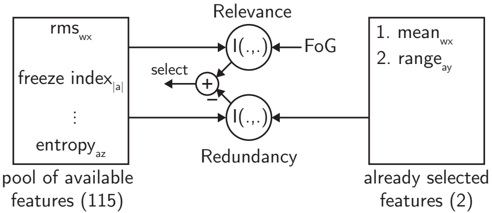

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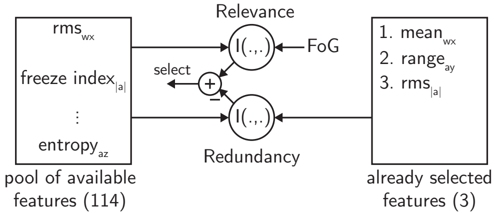

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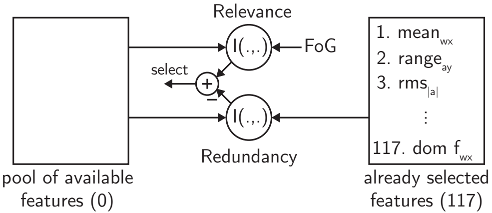

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  where $F_i, i \in [0, n]$ are already selected features
- Conventional wrapper method selecting sub-sets on best performing features

Optimal Feature Subsets

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ML algorithm	Feature Subset
SVM	$\mathrm{FI}_{\|a\|}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{\|w\|}}$, $\overline{a_y}$, SP
Neural Nets	$\mathrm{FI}_{\|a\|}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{w_z}}$, P_{w_z}, S_{a_x}, S_{w_y}, $\overline{a_y}$, R_{w_y}, SP
Log. Regression	$\mathrm{FI}_{\|a\|}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, $\overline{f_{\|w\|}}$, $\overline{a_y}$, $\overline{w_z}$, CV_{a_z}, CV_{a_y}, V, SP
Naïve Bayes	$\mathrm{FI}_{\|a\|}$, LB_{w_z}
k-NN	ST, SL, V, SP
DT (C4.5)	FI_{a_x}, LB_{w_z}, LB_{w_y}, $S_{\|w\|}$, S_{w_z}, $\lceil a_y \rceil$, $\lceil w_z \rceil$, K_{w_x}, K_{a_z}, ST, SL, V, SP
Bagging (C4.5)	FI_{a_x}, LB_{w_z}, $\overline{a_y}$, $\overline{w_z}$, R_{w_y}
Boosting (C4.5)	$\mathrm{FI}_{\|a\|}$, FI_{w_z}, FI_{a_x}, LB_{w_z}, $\overline{f_{w_z}}$, $\overline{f_{\|w\|}}$, DF_{a_y}, $S_{\|w\|}$, $\lceil w_z \rceil$, $\overline{a_y}$,$\overline{w_y}$, K_{w_x}, CV_{a_z}, CV_{w_z}, SL, V, SP
Random Forest	FI_{w_z}, DF_{a_y}, S_{w_z}, $\lceil w_z \rceil$, CV_{w_z}, ST, SL, SP

Legend: $\mathrm{FI}_.$ (freeze index), $\mathrm{LB}_.$ (locomotor band), $S_.$ (entropy), $\overline{f_.}$ (mean frequency), $\mathrm{DF}_.$ (dominant frequency), $\lceil . \rceil$ (maximum value), $\overline{\cdot}$ (mean raw value), $\mathrm{K}_.$ (kurtosis), $\mathrm{CV}_.$ (coefficient of variation), $\mathrm{R}_.$ (range), FoGC (freezing of gait criterion), ST (stride time), SL (stride length), V (velocity), SP (stride peak).

Optimal Feature Subsets

Feature Type	Prevalence
Frequency Domain	**63.83%**
1. freeze index (FI)	27.66%
2. freeze band (FB)	2.13%
3. locomotor band (LB)	2.13%
4. mean frequency (mean f)	2.13%
5. dominant frequency (dom f)	4.26%
6. power	17.02%
7. spectral entropy (entropy)	8.51%
Raw IMU Data	**21.28%**
1. root mean square (rms)	4.26%
2. mean	4.26%
3. standard deviation (std)	4.26%
4. coefficient of variation (CV)	2.13%
5. kurtosis (kurt)	2.13%
6. max	2.13%
7. range	2.13%
Spatio-temporal Domain	**8.51%**
1. stride time	2.13%
2. velocity	2.13%
3. stride length	2.13%
4. FoG Criterion (FoGC)	2.13%
Novel	**0.00%**
1. stride peak	-

ML algorithm	Feature Subset
SVM	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, SP
Neural Nets	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{w_z}}$, P_{w_z}, S_{a_x}, S_{w_y}, $\overline{a_y}$, R_{w_y}, SP
Log. Regression	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, $\overline{w_z}$, CV_{a_z}, CV_{a_y}, V, SP
Naïve Bayes	$\mathrm{FI}_{\lvert a\rvert}$, LB_{w_z}
k-NN	ST, SL, V, SP
DT (C4.5)	FI_{a_x}, LB_{w_z}, LB_{w_y}, $S_{\lvert w\rvert}$, S_{w_z}, $\lceil a_y \rceil$, $\lceil w_z \rceil$, K_{w_x}, K_{a_z}, ST, SL, V, SP
Bagging (C4.5)	FI_{a_x}, LB_{w_z}, $\overline{a_y}$, $\overline{w_z}$, R_{w_y}
Boosting (C4.5)	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{a_x}, LB_{w_z}, $\overline{f_{w_z}}$, $\overline{f_{\lvert w\rvert}}$, DF_{a_y}, $S_{\lvert w\rvert}$, $\lceil w_z \rceil$, $\overline{a_y}$,$\overline{w_y}$, K_{w_x}, CV_{a_z}, CV_{w_z}, SL, V, SP
Random Forest	FI_{w_z}, DF_{a_y}, S_{w_z}, $\lceil w_z \rceil$, CV_{w_z}, ST, SL, SP

Legend: $\mathrm{FI}_.$ (freeze index), $\mathrm{LB}_.$ (locomotor band), $S_.$ (entropy), $\overline{f_.}$ (mean frequency), $\mathrm{DF}_.$ (dominant frequency), $\lceil . \rceil$ (maximum value), $\overline{\cdot}$ (mean raw value), $\mathrm{K}_.$ (kurtosis), $\mathrm{CV}_.$ (coefficient of variation), $\mathrm{R}_.$ (range), FoGC (freezing of gait criterion), ST (stride time), SL (stride length), V (velocity), SP (stride peak).

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1. stride time	2.13%
2. velocity	2.13%
3. stride length	2.13%
4. FoG Criterion (FoGC)	2.13%
Novel	**0.00%**
1. stride peak	-

ML algorithm	Feature Subset
SVM	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, SP
Neural Nets	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{w_z}}$, P_{w_z}, S_{a_x}, S_{w_y}, $\overline{a_y}$, R_{w_y}, SP
Log. Regression	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, $\overline{w_z}$, CV_{a_z}, CV_{a_y}, V, SP
Naïve Bayes	$\mathrm{FI}_{\lvert a\rvert}$, LB_{w_z}
k-NN	ST, SL, V, SP
DT (C4.5)	FI_{a_x}, LB_{w_z}, LB_{w_y}, $S_{\lvert w\rvert}$, S_{w_z}, $\lceil a_y\rceil$, $\lceil w_z\rceil$, K_{w_x}, K_{a_z}, ST, SL, V, SP
Bagging (C4.5)	FI_{a_x}, LB_{w_z}, $\overline{a_y}$, $\overline{w_z}$, R_{w_y}
Boosting (C4.5)	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{a_x}, LB_{w_z}, $\overline{f_{w_z}}$, $\overline{f_{\lvert w\rvert}}$, DF_{a_y}, $S_{\lvert w\rvert}$, $\lceil w_z\rceil$, $\overline{a_y}$,$\overline{w_y}$, K_{w_x}, CV_{a_z}, CV_{w_z}, SL, V, SP
Random Forest	FI_{w_z}, DF_{a_y}, S_{w_z}, $\lceil w_z\rceil$, CV_{w_z}, ST, SL, SP

Legend: $\mathrm{FI}_.$ (freeze index), $\mathrm{LB}_.$ (locomotor band), $S_.$ (entropy), $\overline{f_.}$ (mean frequency), $\mathrm{DF}_.$ (dominant frequency), $\lceil . \rceil$ (maximum value), $\overline{\cdot}$ (mean raw value), $\mathrm{K}_.$ (kurtosis), $\mathrm{CV}_.$ (coefficient of variation), $\mathrm{R}_.$ (range), FoGC (freezing of gait criterion), ST (stride time), SL (stride length), V (velocity), SP (stride peak).

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Spatio-temporal Domain	**8.51%**
1. stride time	2.13%
2. velocity	2.13%
3. stride length	2.13%
4. FoG Criterion (FoGC)	2.13%
Novel	**0.00%**
1. stride peak	-

ML algorithm	Feature Subset
SVM	$\mathrm{FI}_{\|a\|}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{\|w\|}}$, $\overline{a_y}$, SP
Neural Nets	$\mathrm{FI}_{\|a\|}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{w_z}}$, P_{w_z}, S_{a_x}, S_{w_y}, $\overline{a_y}$, R_{w_y}, SP
Log. Regression	$\mathrm{FI}_{\|a\|}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, $\overline{f_{\|w\|}}$, $\overline{a_y}$, $\overline{w_z}$, CV_{a_z}, CV_{a_y}, V, SP
Naïve Bayes	$\mathrm{FI}_{\|a\|}$, LB_{w_z}
k-NN	ST, SL, V, SP
DT (C4.5)	FI_{a_x}, LB_{w_z}, LB_{w_y}, $S_{\|w\|}$, S_{w_z}, $\lceil a_y \rceil$, $\lceil w_z \rceil$, K_{w_x}, K_{a_z}, ST, SL, V, SP
Bagging (C4.5)	FI_{a_x}, LB_{w_z}, $\overline{a_y}$, $\overline{w_z}$, R_{w_y}
Boosting (C4.5)	$\mathrm{FI}_{\|a\|}$, FI_{w_z}, FI_{a_x}, LB_{w_z}, $\overline{f_{w_z}}$, $\overline{f_{\|w\|}}$, DF_{a_y}, $S_{\|w\|}$, $\lceil w_z \rceil$, $\overline{a_y}$,$\overline{w_y}$, K_{w_x}, CV_{a_z}, CV_{w_z}, SL, V, SP
Random Forest	FI_{w_z}, DF_{a_y}, S_{w_z}, $\lceil w_z \rceil$, CV_{w_z}, ST, SL, SP

Legend: $\mathrm{FI}_.$ (freeze index), $\mathrm{LB}_.$ (locomotor band), $S_.$ (entropy), $\overline{f_.}$ (mean frequency), $\mathrm{DF}_.$ (dominant frequency), $\lceil . \rceil$ (maximum value), $\bar{.}$ (mean raw value), $\mathrm{K}_.$ (kurtosis), $\mathrm{CV}_.$ (coefficient of variation), $\mathrm{R}_.$ (range), FoGC (freezing of gait criterion), ST (stride time), SL (stride length), V (velocity), SP (stride peak).

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4. FoG Criterion (FoGC)	2.13%
Novel	**0.00%**
1. stride peak	-

ML algorithm	Feature Subset
SVM	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, SP
Neural Nets	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{w_z}}$, P_{w_z}, S_{a_x}, S_{w_y}, $\overline{a_y}$, R_{w_y}, SP
Log. Regression	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, $\overline{w_z}$, CV_{a_z}, CV_{a_y}, V, SP
Naïve Bayes	$\mathrm{FI}_{\lvert a\rvert}$, LB_{w_z}
k-NN	ST, SL, V, SP
DT (C4.5)	FI_{a_x}, LB_{w_z}, LB_{w_y}, $S_{\lvert w\rvert}$, S_{w_z}, $\lceil a_y\rceil$, $\lceil w_z\rceil$, K_{w_x}, K_{a_z}, ST, SL, V, SP
Bagging (C4.5)	FI_{a_x}, LB_{w_z}, $\overline{a_y}$, $\overline{w_z}$, R_{w_y}
Boosting (C4.5)	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{a_x}, LB_{w_z}, $\overline{f_{w_z}}$, $\overline{f_{\lvert w\rvert}}$, DF_{a_y}, $S_{\lvert w\rvert}$, $\lceil w_z\rceil$, $\overline{a_y}$,$\overline{w_y}$, K_{w_x}, CV_{a_z}, CV_{w_z}, SL, V, SP
Random Forest	FI_{w_z}, DF_{a_y}, S_{w_z}, $\lceil w_z\rceil$, CV_{w_z}, ST, SL, SP

Legend: $\mathrm{FI}_.$ (freeze index), $\mathrm{LB}_.$ (locomotor band), $S_.$ (entropy), $\overline{f_.}$ (mean frequency), $\mathrm{DF}_.$ (dominant frequency), $\lceil . \rceil$ (maximum value), $\bar{.}$ (mean raw value), $\mathrm{K}_.$ (kurtosis), $\mathrm{CV}_.$ (coefficient of variation), $\mathrm{R}_.$ (range), FoGC (freezing of gait criterion), ST (stride time), SL (stride length), V (velocity), SP (stride peak).

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Spatio-temporal Domain	**8.51%**
1. stride time	2.13%
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4. FoG Criterion (FoGC)	2.13%
Novel	**0.00%**
1. stride peak	-

ML algorithm	Feature Subset
SVM	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, SP
Neural Nets	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{w_z}}$, P_{w_z}, S_{a_x}, S_{w_y}, $\overline{a_y}$, R_{w_y}, SP
Log. Regression	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, $\overline{w_z}$, CV_{a_z}, CV_{a_y}, V, SP
Naïve Bayes	$\mathrm{FI}_{\lvert a\rvert}$, LB_{w_z}
k-NN	ST, SL, V, SP
DT (C4.5)	FI_{a_x}, LB_{w_z}, LB_{w_y}, $S_{\lvert w\rvert}$, S_{w_z}, $\lceil a_y \rceil$, $\lceil w_z \rceil$, K_{w_x}, K_{a_z}, ST, SL, V, SP
Bagging (C4.5)	FI_{a_x}, LB_{w_z}, $\overline{a_y}$, $\overline{w_z}$, R_{w_y}
Boosting (C4.5)	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{a_x}, LB_{w_z}, $\overline{f_{w_z}}$, $\overline{f_{\lvert w\rvert}}$, DF_{a_y}, $S_{\lvert w\rvert}$, $\lceil w_z \rceil$, $\overline{a_y}$,$\overline{w_y}$, K_{w_x}, CV_{a_z}, CV_{w_z}, SL, V, SP
Random Forest	FI_{w_z}, DF_{a_y}, S_{w_z}, $\lceil w_z \rceil$, CV_{w_z}, ST, SL, SP

Legend: $\mathrm{FI}_.$ (freeze index), $\mathrm{LB}_.$ (locomotor band), $S_.$ (entropy), $\overline{f_.}$ (mean frequency), $\mathrm{DF}_.$ (dominant frequency), $\lceil . \rceil$ (maximum value), $\overline{.}$ (mean raw value), $\mathrm{K}_.$ (kurtosis), $\mathrm{CV}_.$ (coefficient of variation), $\mathrm{R}_.$ (range), FoGC (freezing of gait criterion), ST (stride time), SL (stride length), V (velocity), SP (stride peak).

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Spatio-temporal Domain	**8.51%**
1. stride time	2.13%
2. velocity	2.13%
3. stride length	2.13%
4. FoG Criterion (FoGC)	2.13%
Novel	**0.00%**
1. stride peak	-

ML algorithm	Feature Subset
SVM	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, SP
Neural Nets	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{w_z}}$, P_{w_z}, S_{a_x}, S_{w_y}, $\overline{a_y}$, R_{w_y}, SP
Log. Regression	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, $\overline{w_z}$, CV_{a_z}, CV_{a_y}, V, SP
Naïve Bayes	$\mathrm{FI}_{\lvert a\rvert}$, LB_{w_z}
k-NN	ST, SL, V, SP
DT (C4.5)	FI_{a_x}, LB_{w_z}, LB_{w_y}, $S_{\lvert w\rvert}$, S_{w_z}, $\lceil a_y \rceil$, $\lceil w_z \rceil$, K_{w_x}, K_{a_z}, ST, SL, V, SP
Bagging (C4.5)	FI_{a_x}, LB_{w_z}, $\overline{a_y}$, $\overline{w_z}$, R_{w_y}
Boosting (C4.5)	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{a_x}, LB_{w_z}, $\overline{f_{w_z}}$, $\overline{f_{\lvert w\rvert}}$, DF_{a_y}, $S_{\lvert w\rvert}$, $\lceil w_z \rceil$, $\overline{a_y}$,$\overline{w_y}$, K_{w_x}, CV_{a_z}, CV_{w_z}, SL, V, SP
Random Forest	FI_{w_z}, DF_{a_y}, S_{w_z}, $\lceil w_z \rceil$, CV_{w_z}, ST, SL, SP

Legend: $\mathrm{FI}_.$ (freeze index), $\mathrm{LB}_.$ (locomotor band), $S_.$ (entropy), $\overline{f_.}$ (mean frequency), $\mathrm{DF}_.$ (dominant frequency), $\lceil . \rceil$ (maximum value), $\overline{\cdot}$ (mean raw value), $\mathrm{K}_.$ (kurtosis), $\mathrm{CV}_.$ (coefficient of variation), $\mathrm{R}_.$ (range), FoGC (freezing of gait criterion), ST (stride time), SL (stride length), V (velocity), SP (stride peak).

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Novel	**0.00%**
1. stride peak	-

ML algorithm	Feature Subset
SVM	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, SP
Neural Nets	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{w_z}}$, P_{w_z}, S_{a_x}, S_{w_y}, $\overline{a_y}$, R_{w_y}, SP
Log. Regression	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, $\overline{w_z}$, CV_{a_z}, CV_{a_y}, V, SP
Naïve Bayes	$\mathrm{FI}_{\lvert a\rvert}$, LB_{w_z}
k-NN	ST, SL, V, SP
DT (C4.5)	FI_{a_x}, LB_{w_z}, LB_{w_y}, $S_{\lvert w\rvert}$, S_{w_z}, $\lceil a_y \rceil$, $\lceil w_z \rceil$, K_{w_x}, K_{a_z}, ST, SL, V, SP
Bagging (C4.5)	FI_{a_x}, LB_{w_z}, $\overline{a_y}$, $\overline{w_z}$, R_{w_y}
Boosting (C4.5)	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{a_x}, LB_{w_z}, $\overline{f_{w_z}}$, $\overline{f_{\lvert w\rvert}}$, DF_{a_y}, $S_{\lvert w\rvert}$, $\lceil w_z \rceil$, $\overline{a_y}$,$\overline{w_y}$, K_{w_x}, CV_{a_z}, CV_{w_z}, SL, V, SP
Random Forest	FI_{w_z}, DF_{a_y}, S_{w_z}, $\lceil w_z \rceil$, CV_{w_z}, ST, SL, SP

Legend: $\mathrm{FI}_.$ (freeze index), $\mathrm{LB}_.$ (locomotor band), $S_.$ (entropy), $\overline{f_.}$ (mean frequency), $\mathrm{DF}_.$ (dominant frequency), $\lceil . \rceil$ (maximum value), $\overline{.}$ (mean raw value), $\mathrm{K}_.$ (kurtosis), $\mathrm{CV}_.$ (coefficient of variation), $\mathrm{R}_.$ (range), FoGC (freezing of gait criterion), ST (stride time), SL (stride length), V (velocity), SP (stride peak).

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Novel	**0.00%**
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ML algorithm	Feature Subset
SVM	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, SP
Neural Nets	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, LB_{a_x}, $\overline{f_{w_z}}$, P_{w_z}, S_{a_x}, S_{w_y}, $\overline{a_y}$, R_{w_y}, SP
Log. Regression	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{w_y}, LB_{w_z}, $\overline{f_{\lvert w\rvert}}$, $\overline{a_y}$, $\overline{w_z}$, CV_{a_z}, CV_{a_y}, V, SP
Naïve Bayes	$\mathrm{FI}_{\lvert a\rvert}$, LB_{w_z}
k-NN	ST, SL, V, SP
DT (C4.5)	FI_{a_x}, LB_{w_z}, LB_{w_y}, $S_{\lvert w\rvert}$, S_{w_z}, $\lceil a_y \rceil$, $\lceil w_z \rceil$, K_{w_x}, K_{a_z}, ST, SL, V, SP
Bagging (C4.5)	FI_{a_x}, LB_{w_z}, $\overline{a_y}$, $\overline{w_z}$, R_{w_y}
Boosting (C4.5)	$\mathrm{FI}_{\lvert a\rvert}$, FI_{w_z}, FI_{a_x}, LB_{w_z}, $\overline{f_{w_z}}$, $\overline{f_{\lvert w\rvert}}$, DF_{a_y}, $S_{\lvert w\rvert}$, $\lceil w_z \rceil$, $\overline{a_y}$,$\overline{w_y}$, K_{w_x}, CV_{a_z}, CV_{w_z}, SL, V, SP
Random Forest	FI_{w_z}, DF_{a_y}, S_{w_z}, $\lceil w_z \rceil$, CV_{w_z}, ST, SL, SP

Legend: $\mathrm{FI}_.$ (freeze index), $\mathrm{LB}_.$ (locomotor band), $S_.$ (entropy), $\overline{f_.}$ (mean frequency), $\mathrm{DF}_.$ (dominant frequency), $\lceil . \rceil$ (maximum value), $\overline{.}$ (mean raw value), $\mathrm{K}_.$ (kurtosis), $\mathrm{CV}_.$ (coefficient of variation), $\mathrm{R}_.$ (range), FoGC (freezing of gait criterion), ST (stride time), SL (stride length), V (velocity), SP (stride peak).

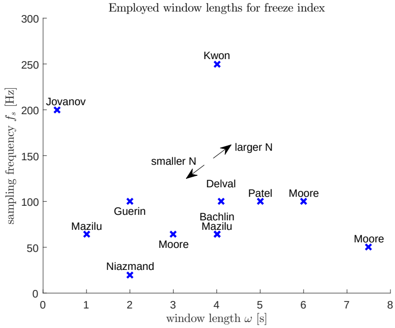
Performance Evaluation

Feature sets	Our	Bächlin	Mazilu	Tripoliti	Coste
Feature Count	2-17	2	7	3	1
$\omega \in \mathcal{W}, N \in \mathcal{N}$	100%	50%	14.2%	0%	-

Machine learning algorithms

SVM
Neural Nets
Log. Regression
Naive Bayes
k-NN
DT (C4.5)
Bagging (C4.5)
Boosting (C4.5)
Random Forest

Average



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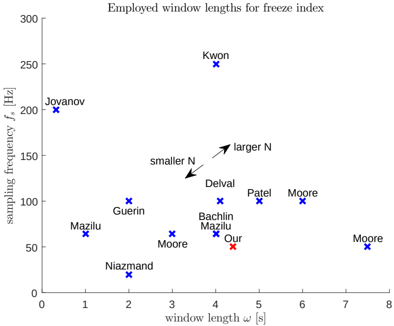

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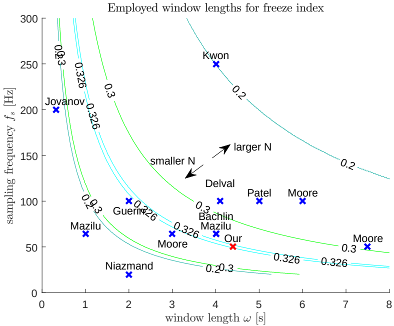

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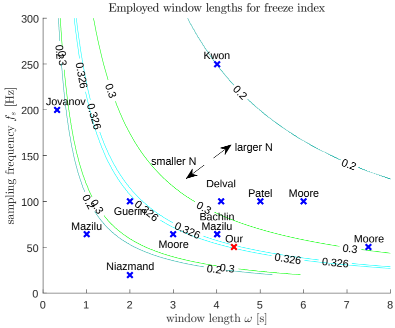
Machine learning algorithms					
SVM	**0.880**	0.860	0.862	0.800	0.782
Neural Nets	**0.872**	0.859	0.852	0.747	0.745
Log. Regression	**0.880**	0.857	0.861	0.811	0.774
Naive Bayes	**0.875**	0.867	0.795	0.782	0.785
k-NN	**0.801**	0.797	0.800	0.678	0.709
DT (C4.5)	**0.845**	0.838	0.809	0.770	0.700
Bagging (C4.5)	**0.852**	0.842	0.824	0.751	0.702
Boosting (C4.5)	**0.871**	0.821	0.834	0.727	0.700
Random Forest	**0.878**	0.824	0.832	0.738	0.709
Average	**0.861**	0.841	0.830	0.756	0.734



- **Feature selection creates favorable subsets** that outperform the arbitrary assembled feature sets in literature.

Conclusion

Purpose revisited.

Conclusion

1. **Feature Extraction:**
   - What are the optimum window lengths?
   - Does the window length affect classification performance?
2. **Feature Selection:**
   - Given all published IMU features for FOG detection, what are good subset thereof?
   - How do these compare against previously published feature sets?

Conclusion

1. **Feature Extraction:**
   - What are the optimum window lengths?

     Identified the optimal window length for 117 features.
   - Does the window length affect classification performance?

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Conclusion

1. **Feature Extraction:**
   - What are the optimum window lengths?

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     It significantly affects classification performance for the majority of features.

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   - Given all published IMU features for FOG detection, what are good subset thereof?

     The feature subsets have been found for 9 machine learning algorithms.
   - How do these compare against previously published feature sets?

     Extraction at optimal window lengths and feature selection creates favorable classification performance.

Thank you!

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