

# Robust multi-dimensional motion features for first-person vision activity recognition

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Authors: Girmaw Abebe, Andrea Cavallaro, Xavier Parra

Centre for Intelligent Sensing  
Queen Mary University of London

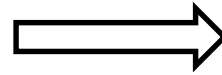
# Introduction

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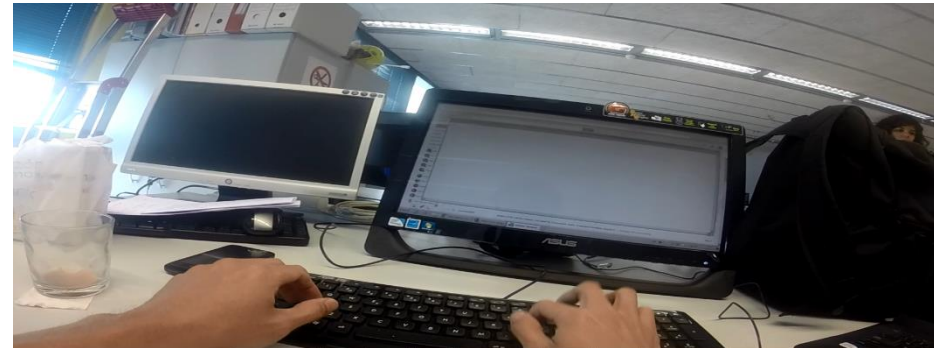
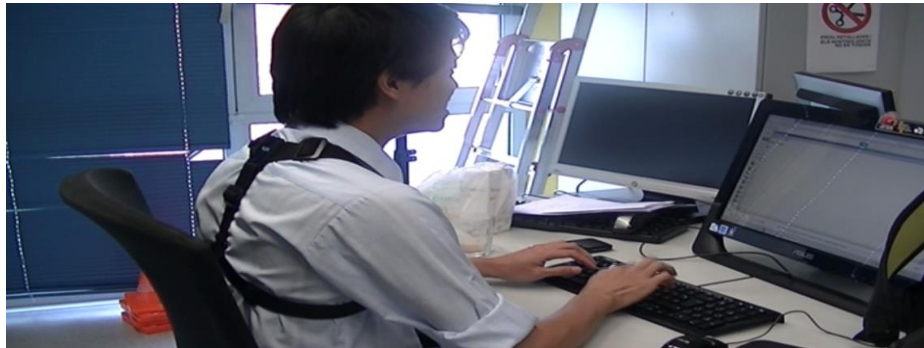
Third-person vision

Sensing is external



First-person vision

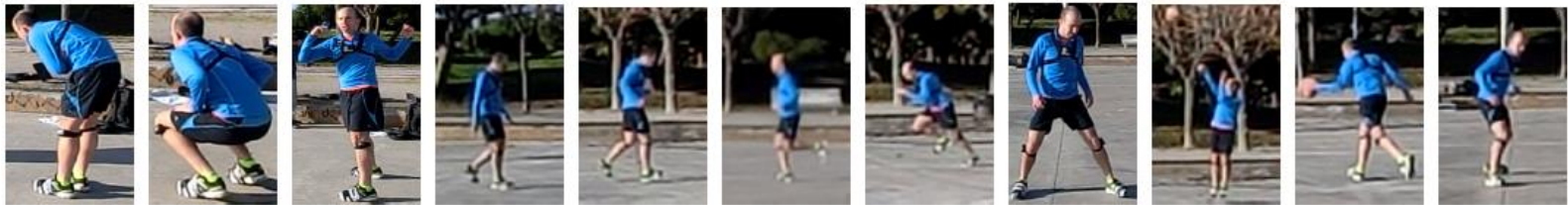
Sensing is ego-centric



# Problem definition

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- Given first-person videos of ambulatory activities, we develop a robust motion feature in order to recognize the activities
- Ambulatory activities involve full-body motions



Third-person view

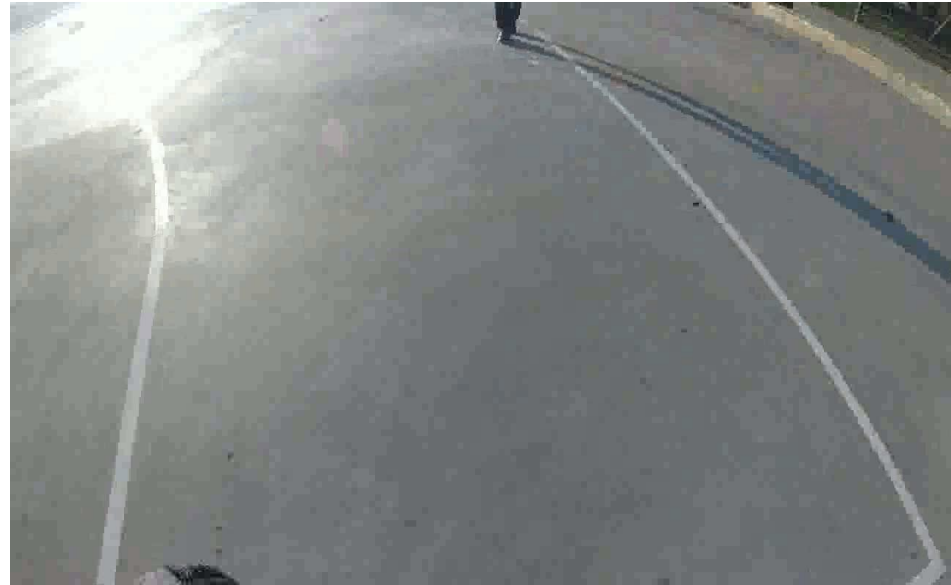


First-person view

# Challenges

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- Complex ego-motion
- Motion parallax and blur
  - E.g., Dribble and Sprint
- Local motions
  - E.g., Appearance of people
- Mounting point variations
  - E.g., Chest vs Head
- Limited datasets



# Related work: acquisition

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- Acquisition device
  - Lab prototypes [zhang2010,2011, Zhan2012,2014,2015, Nam2013]
  - Commercial cameras [Ryoo2015, Kitani2011, Poleg2016, Poleg2014]
- Mounting positions
  - Head mounts [Kitani2011, Poleg2016, Poleg2014]
  - Chest [zhang2010,2011]
  - Wrist [Nam2013]
- Preprocessing
  - Data resizing
  - Filtering



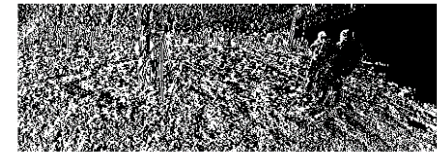
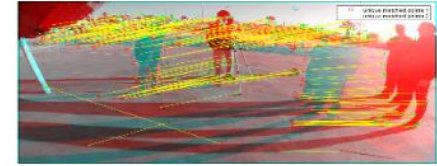
[zhang2010,2011]



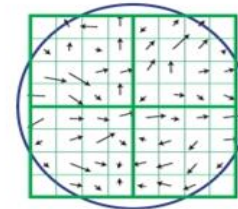
[Poleg2014]

# Related work: feature extraction

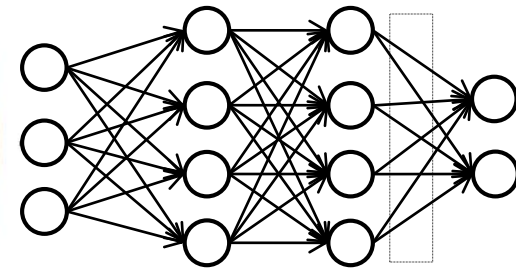
- Keypoint-based [zhang2010,2011]
- Optical flow-based
  - Grid optical flow [Zhan2012,2014, Nam2013, Poleg2014]
  - Magnitude [Kitani2011]
  - Direction [Ryoo2013,2015, Iwashita2014]
  - Frequency domain analysis [Kitani2011]



- Intra-frame appearance [Kitani2014,Ryoo2015]

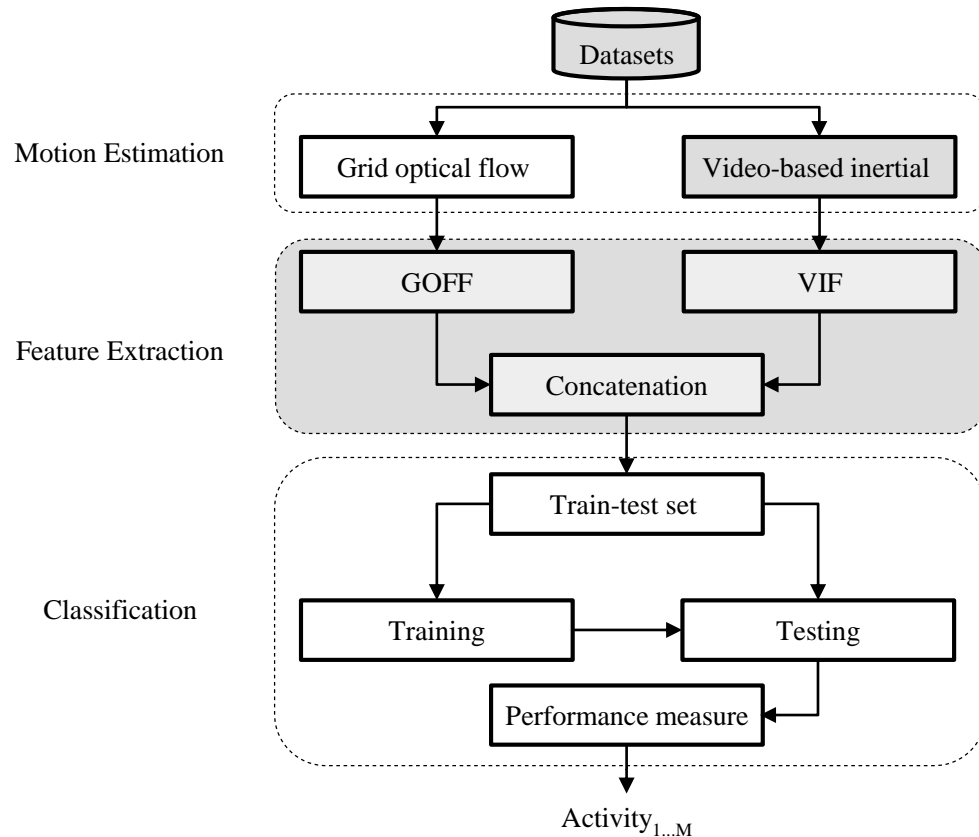


[Lowe1999]



# Proposed approach

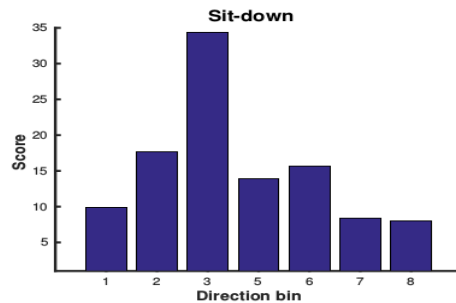
- Encode significant motion variations
- Generate virtual inertial features
- Multiple validation



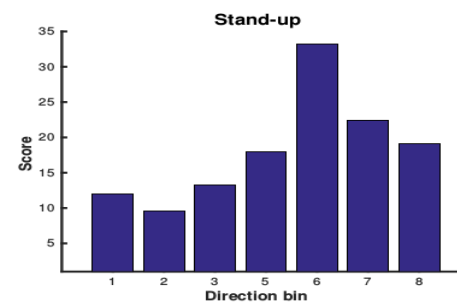
- Contributions are highlighted

# Grid Features: examples

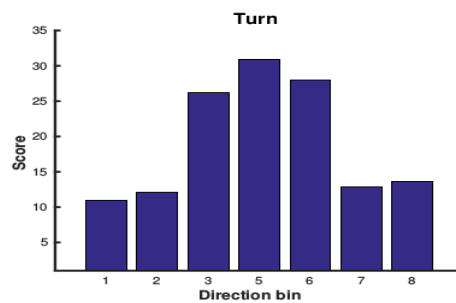
- Proposed features are shown to discriminate activities.
  - E.g., MDHF: motion-direction histogram feature



(a)



(b)



(c)

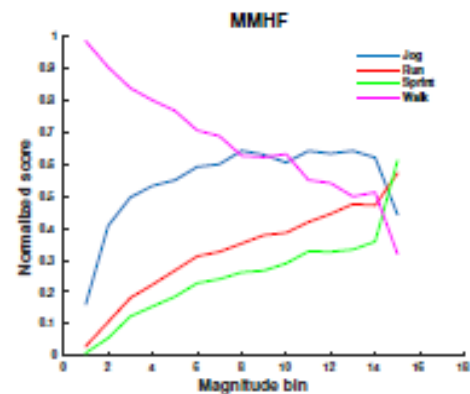
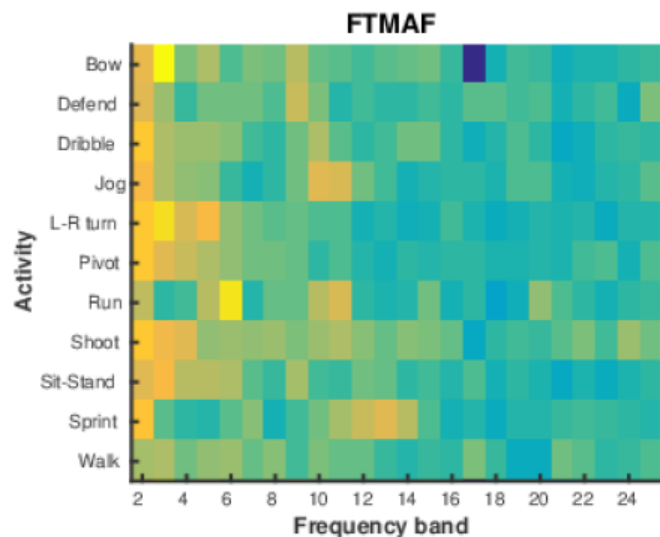


(d)



# Grid Features: more examples

- Frequency feature of motion direction (FTMAF)



- Motion magnitude histogram (FTMAF)

# Evaluation

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- Datasets

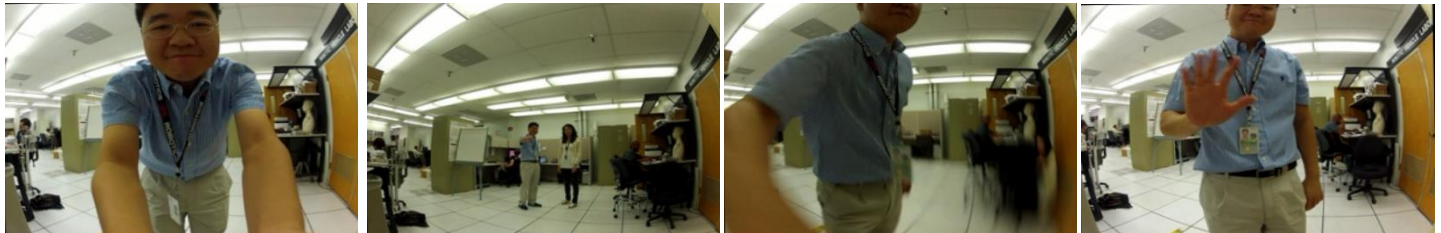
- IAR



- BAR



- JPL  
[Ryoo2013]



- DogC  
[Iwashita2014]



# Results on our datasets

Dataset	Method	A	P	R	S	F <sub>1</sub>	KNN
IAR	AP [zhan2015]	92	85	42	<b>99</b>	56	49
	MRGF [zhang2011]	97	90	<b>87</b>	98	<b>88</b>	<b>79</b>
	MBH [Kitani2011]	91	62	68	94	65	67
	<b>RMF (Proposed)</b>	<b>97</b>	<b>91</b>	85	<b>99</b>	<b>88</b>	<b>78</b>
BAR	AP [zhan2015]	90	24	14	97	18	31
	MRGF [zhang2011]	89	35	39	93	37	48
	MBH [Kitani2011]	95	63	67	97	64	71
	<b>RMF (Proposed)</b>	<b>98</b>	<b>81</b>	<b>79</b>	<b>99</b>	<b>80</b>	<b>78</b>

Key:

A: Accuracy

P: Precision

R: Recall

S: Specificity

F<sub>1</sub>: F-score

KNN: Recall output  
of KNN classifier

# Results on public datasets

Dataset	Method	A	P	R	S	F <sub>1</sub>	KNN
JPL	AP [zhan2015]	76	5	16	86	7	34
	MRGF [zhang2011]	85	55	72	87	62	55
	MBH [Kitani2011]	87	66	53	92	59	61
	<b>RMF (Proposed)</b>	<b>96</b>	<b>87</b>	<b>85</b>	<b>97</b>	<b>86</b>	<b>82</b>
DogC	AP [zhan2015]	87	39	30	92	34	47
	MRGF [zhang2011]	88	39	39	94	39	42
	MBH [Kitani2011]	86	38	27	92	32	51
	<b>RMF (Proposed)</b>	<b>92</b>	<b>62</b>	<b>59</b>	<b>96</b>	<b>61</b>	<b>58</b>

Key:

A: Accuracy

P: Precision

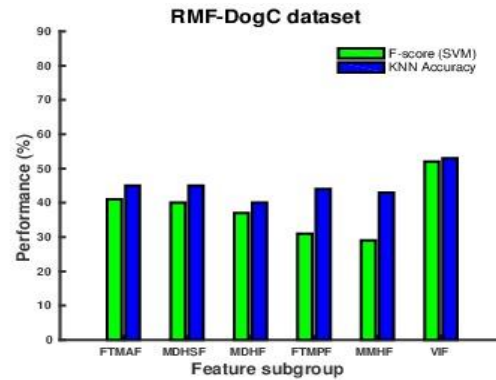
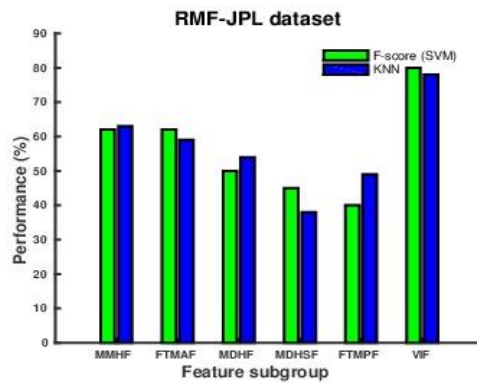
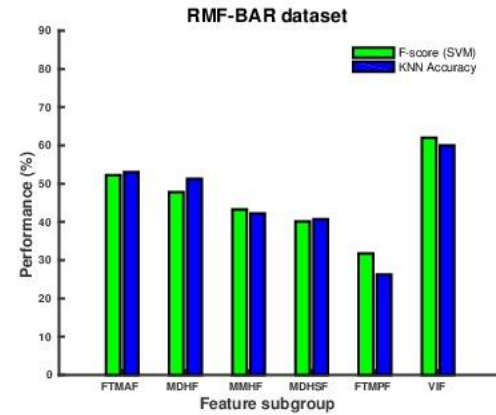
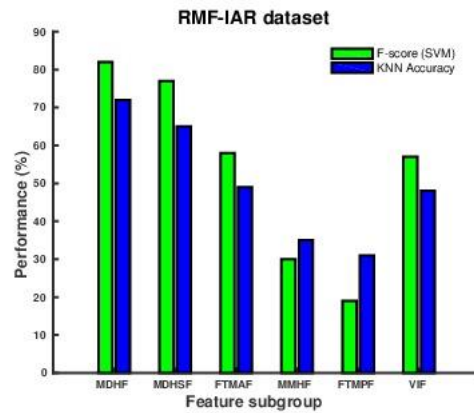
R: Recall

S: Specificity

F<sub>1</sub>: F-score

KNN: Recall output of KNN classifier

# Discussion: features



# Summary

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- Multi-dimensional motion features encode direction, magnitude and dynamics
- Inertial features generated from video proven to be useful
- Collection of new publicly available datasets
- **Limitations:** small datasets, mounting positions (self-occlusions)

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Thank you!  
Questions?