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Putting AI to Work: Improving Patient Safety with Wearable Sensors

Ismail Uysal, Ph.D.

Associate Professor & Undergraduate Director Electrical Engineering @ University of South Florida Tampa, FL, USA

09/22/2022 - Thursday

A quick word about my university...

University of South Florida – Bull Pride !

- Ranked in the **top-25** universities worldwide for granted U.S. patents (Intellectual Property Owners Association) in 2022.
 - And **top-15** in the United States for the 10th consecutive year !.
- **\$568.1 million** in externally funded research grants and contracts in FY 2021 (during the pandemic) !
- Consistent and strong emphasis on « **applied research** », strong collaborations and partnerships with industry !



Electrical Engineering @ USF

- 600 students (350 UG and 250 G ~ 100 Ph.D. students)
- Over \$5.5M/yr. in annual research (largest in the College)
- 4 IEEE Fellows
- 1 National Academy of Engineers Member / Dr. Rich Gitlin as Emeritus Faculty





12th Year with RFID Journal !

- We believe that applied academic research is a key component of any innovation.
- RFID/IoT some of the most innovative technologies of the past decade.
- We also believe academia and industry can and **should** work together to achieve the best outcome for any implementation.
- So...we're glad to be a part of this community since 2010 ©





A 3-point research triangle for me...

- Ph.D. work @ Univ. of Florida in "speech recognition" and "bio-inspired signal processing" and "machine learning".
- Postdoc @ UF & USF on "*RFID communications*" and "*RFID-based remote sensing applications*".
- And now, there and back again: concentrating on fusion of both fields as front-end/back-end technologies.



Thanks to the sponsors over the years...





I would also like to thank my Ph.D. students who have done most of the work presented today !

- Ria Kanjilal (Ph.D., 2022) ***
- Ismail Uluturk (Ph.D., 2020) ***
- Ozsel Kilinc (Ph.D., 2018)
- This work is sponsored in part by Florida High Tech Corridor Research Grant FHT 19-06 titled "Algorithmic Prediction and Recognition of Human Activity and Falls from Wireless Accelerometer Data".
- *** 2020 Excellence in Student Research Award





Machine Intelligence for Sensor

Applications

Fall Detection & Human Activity Recognition with Wireless Accelerometers





How can IoT and AI help?





But first – is there a need for help?

- U.S. Department of Health and Human Sciences, predicts approximately 90 million people in the US aged 65 or older by 2050.
- Falls are the leading cause of both fatal and non-fatal injuries among older adults.
- Study of Center for Disease Control and Prevention (CDC) says death rate has increased ~ 31% from 2007 to 2016.
- Global market for home healthcare technologies used in elder care should grow from \$5.7 billion in 2017 to \$13.6 billion by 2022
- A wireless wrist-band with a fall-detection algorithm can prevent a person from lying in the emergency room for hours or days.



The <u>AI in Healthcare</u> market will pass \$35 billion by 2030 – almost doubling every year.



Research objectives

- Can we detect and identify falls using only 3-axis accelerometer time data coming from standard wireless/RFID wrist brands?
- Can we do more detect the type of motion based on the same data to assist in proactive interventions or proper physical therapy?





How does the system work (at a high level)?





Always begin with the same question: What does the data look like?







Just looking at the raw data is not very helpful !

- Need to extract meaningful information.
- We call this "feature extraction"
- These features could be:
 - simple statistical measures,
 - or something more complicated !





Taking simple average







Or looking at standard deviation...







When simple measures are not enough...

$$pitch = \arctan(\frac{x_N}{\sqrt{y_N^2 + z_N^2}}) - \arctan(\frac{x_1}{\sqrt{y_1^2 + z_1^2}})$$

$$roll = \arctan(\frac{y_N}{\sqrt{x_N^2 + z_N^2}}) - \arctan(\frac{y_1}{\sqrt{x_1^2 + z_1^2}})$$

$$yaw = \arctan(\frac{z_N}{\sqrt{x_N^2 + y_N^2}}) - \arctan(\frac{z_1}{\sqrt{x_1^2 + y_1^2}})$$

SOUTH FLORIDA

Do they make a difference?







And a little bit of the "intuitive" features (!)





Do they help?







Our early research found that using these features together is better !

Used Features	Accuracy %
Mean(x,y,z), Variance(x,y,z)	60.5
Mean(x,y,z), Variance(x,y,z), PRY	66.9
Mean(x,y,z), Variance(x,y,z), PRY, MCR	81
Mean(x,y,z), Variance(x,y,z), PRY, MCR, FCR	82.6





Question is – how do we use them together?

- Artificial intelligence !
- We are doing pattern recognition.
- To "recognize" means to correctly classify a sample based on its class label.
- Two classifiers:
 - Support vector machines
 - Artificial neural networks





A quick diversion: Machine Learning





Machine Learning – a 2-minute history !

- Arthur Samuel in 1959:
 - The field of study that enables the computers to learn without being "explicitly" programmed.
 - His algorithm learned to play checkers
 - He couldn't win against his own algorithms which means he actually won as a scientist ! ⁽²⁾
- Tom Mitchell later provided my favorite definition:
 - P on T improves with E.
 - In other words: "An algorithm which can learn from an experience (E) with respect to a task (T) and performance (P) such that P on T improves with E.





Started with linear regression (y = a.x + b) and morphed into something more...





How do they learn?



If this is a dog...



And this is a cat...



What is this?



Where are we now?



A baseball game in progress.



A person holding a cell phone in their hand.



A brown bear standing on top of a lush green field.



A close up of a person brushing his teeth.



What was once fiction...





Now a reality...



Same story in many areas..

Speech recognition

- What started out as an embarrassment (~30% word error rate, failed demonstrations in front of large audiences...)
- Turned into an incredible success story:
 - Google Word Error Rate: 4.9%
 - Human Word Error Rate: ~5%

• Generative models

- An indicator of true AI?
- None of the people on this slide are real people !
- They are generated by a technique called generative adversarial models...







We work on pretty cool stuff, too...





Apologies for the diversion $\ensuremath{\mathfrak{O}}$

• Let's get back to where we were with some results...





Results on fall detection (limited dataset)

- Publicly available datasets are not readily available on patient falls using accelerometers.
 - We would be more than willing to partner if you have a facility where we can collect and analyze real data !
- Limited dataset obtained using real wireless wristbands in an actual hospital in Turkey.
- 100% accuracy with <u>no false positives</u> (identify a fall when there is none) or <u>false negatives</u> (miss a fall when someone did).





More complicated motion recognition

- Publicly available UniMiB-SHAR dataset
 - 11771 samples for fall data (Labeled as AF-2, Action vs Fall Binary)
 - 30 different users
 - Three-axis acceleration data from simple sensors



For our application, we need something powerful...



Just like a human being, you train a neural network by showing examples and telling it which class they belong to.

Through iterative learning process, the neural network learns over time to identify different data samples.

And then you test it on samples it has never seen before !



Does the model work?

- Using the previously used features we get:
 - 96.85% accuracy on this particular dataset
 - Better than state-of-the-art reported on this dataset
 - But not necessarily error-free (!)





Shall we try something else? Did someone say Deep Learning?

- What is so special about Deep Learning for this application?
- No complicated feature extractions let the algorithm learn everything from raw, unfiltered data



- Easy right?
- Perhaps not...



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How does it work?







Does complexity help?

Yes – as long as you keep in mind it is never an **exact science to choose the best settings with data-driven machine learning.**

Does that remind you of another technology? ©

99.01% - best results reported so far on this fall detection dataset

Data	HL1	HL2	HL3	HL4	HL5	Mean Acc raw data (%)
	500					98.76
AF-2	500	500				98.64
11771	250	250	50			98.89
observa	250	250	50	20		99.01
-tions	250	250	50	50	20	98.51



Can it be used for more than simply detecting patient falls?

We anticipate...if we can scale beyond binary detections of fall versus no-fall, there are tremendous applications in healthcare !

- Recognize daily activities
- Assist in physical therapy of elderly patients
- Welfare checks and automated reporting
- Preemptive diagnosis and detection of falls or movement issues.





- UniMiB-SHAR Dataset
- 9 different activity classes
- 7579 observations from 30 different subjects
- Labeled as A-9 (9 different action classes)







Is the new technology better?

Data	HL1	HL2	HL3	HL4	HL5	Mean Acc raw data (%)	Mean Acc fea- tures (%)
	500					87.79	91.61
A-9	500	500				87.86	92.07
7579	250	250	50			88.20	93.79
observa	250	250	50	20		85.75	91.87
-tions	250	250	50	50	20	84.83	92.05

- Highest reported accuracy in the literature is 88.41%
- Highest accuracy we could obtain is 88.20%
- Shall we go back to features – what is wrong?





Let's step back...and look at a commercially successful example for deep learning...

- Speech recognition...
- How do they do it ?
- Google, Apple, Facebook, Microsoft, etc. all use the same underlying technology called...
- Recurrent Neural Networks (RNNs) which operate on temporal (timebased) data...
- Data format for fall detection/activity recognition?
- You guessed it: time based !





Does it help?

Mean accuracy of RNN-LSTM model on UniMiB-SHAR dataset

Data	HL1	HL2	HL3	HL4	HL5	Mean Acc raw data (%)	Mean Acc fea- tures (%)
	500					94.13	95.78
	500	500				97.89	95.84
A-9	250	250	50			97.96	96.35
	250	250	50	20		98.02	95.84
	250	250	50	50	20	97.11	95.75

As a quick reminder: state-of-the-art on this dataset was 88.41%

Our best performance was 88.20%

Best performance we got using RNN on raw, unfiltered time-domain acceleration data is **98.02%**

Best results reported in the literature for human activity recognition on this dataset !



Hot off the press (!) – What about different sensor placements?

- Adult-Youth Dataset. Presented by a group of activity recognition researchers at Stanford [Mannini et al.]
- Large number of participants with different sensor placements
 - 53 Participants 33 Adults; 20 Youths
 - Wrist & ankle sensors
 - Activities measured in 3-5 minutes window



Dataset	Observations
Adult-ankle	12812
Adult-wrist	12618
Youth-ankle	7910
Youth-wrist	7869

Remember the approach



Did it work?

Yes – but, not state-of-the-art ! ☺

	Average classification accuracy (%)							
Classifier	Adult-ankle	Adult-wrist	Youth-ankle	Youth-wrist				
1D-CNN	95.21 ± 2.38	88.02 ± 6.29	88.49 ± 8.98	90.54 ± 4.98				
Mannini et al. [22]	94.8	87	92.4	91				



Can we get even fancier with our data?





Need an even deeper approach – Convolutional Neural Networks (CNNs)





Does it work? Yes !





	Average classification accuracy (%)							
Classifier	Adult-ankle	Adult-wrist	Youth-ankle	Youth-wrist				
DFNN	91.17 ± 3.47	87.43 ± 7.87	$85.86 \!\pm\! 10.43$	88.30 ± 8.3				
AE-DFNN	88.33 ± 4.81	81.31 ± 7.74	$82.68 \!\pm\! 10.78$	80.81 ± 8.04				
1D-CNN	95.21 ± 2.38	88.02 ± 6.29	88.49 ± 8.98	90.54 ± 4.98				
2D-CNN	$95.57{\pm}2.54$	$93.45{\pm}3.55$	$93.38{\pm}2.67$	$\textbf{93.13} \pm \textbf{3.5}$				
Mannini et al. [22]	94.8	87	92.4	91				
FE-DFNN [11]	92 ± 4.38	83.78 ± 8.45	85.79 ± 9.82	85.86 ± 8.47				

Best results reported in the literature on this dataset as of today...



Not all challenges are created equal...

Remember there are 53 subjects and some of them have very low accuracies...

Subject Specific Modeling (SSM)

SubTransfer Modeling (STM)





UNIVERSITY of

COMPUTATIONAL COMPLEXITIES OF FIVE CLASSIFIERS FOR A SINGLE SUBJECT ON FOUR DATASETS

	Data	Subject	Classifier	Accuracy	Epochs	Training	Test	Computational	Computational	Training
				(%)		Time (S)	Time	Time (S)	Time/epoch	Parameters
							(S)		(S)	
			DFNN	95.15	200	159	0.11	159.11	0.8	750754
			AE-DFNN	90.61	1700	1528.95	1.607	1530.56	0.9	2796617
			(AE + DFNN)							
	Adult-	14	1D-CNN	97.58	1000	15589.27	0.25	15589.53	15.59	7257646
	ankle									
			2D-CNN	98.49	500	368.2	0.18	368.38	0.74	1674632
			RNN-LSTM	99.7	100	246182.98	13.77	246196.74	2461.97	815404
			DFNN	82.25	1500	1132.2	0.11	1132.32	0.76	750754
All about			AE-DFNN	53.84	1700	1018.30	1.55	1019.85	0.6	2796617
All about			(AE + DFNN)		1000	1 5000 50		1.5000.1.6		
	Adult-	7	1D-CNN	82.61	1000	15099.22	0.24	15099.46	15.1	7257646
spood	wrist			05.05						1 (2) (2)
Sheen			2D-CNN	85.87	800	577.52	0.204	577.72	0.72	16/4632
•			RNN-LSTM	64.86	150	386677.11	10.42	386687.54	2577.92	815404
			DFNN	85.08	1200	575.75	0.11	575.86	0.48	750754
			AE-DFNN	76.82	1700	637.42	0.86	638.28	0.38	2796617
			(AE + DFNN)	01.5	1000	0500.00	0.05	05/7 10	0.57	
	Youth-	3	ID-CNN	81.5	1000	9566.86	0.25	9567.12	9.57	7257646
	ankle			07.16	200	271 (4	0.01	271.04	0.47	1(74(22)
			2D-CININ DNIN L STM	87.10	800	3/1.04	0.21	3/1.84	0.4/	10/4032
			KININ-LSTIVI	92.24	100	130094.10	15.45	130107.39	1301.08	813404
			DFININ AE DENINI	93.4	1500	699.62	0.1	699.72	0.47	750754
			AE-DFININ	/8./2	1700	023.009	0.859	023.808	0.307	2/9001/
	Vouth	4	(AE + DFNN)	00.91	1500	14107 6	0.12	14107 72	0.47	7257616
	ioun-	4	ID-CININ	90.81	1500	14197.0	0.15	14197.75	9.47	123/040
	wrist		2D CNN	04.25	620	280.7	0.21	280.01	0.45	1674622
			2D-CININ DNIN I STM	94.25	100	200.7 137337 16	11 17	127248 22	1272 / 8	1074032 815404
			1/11/-1/2 1 1/1	07.77	100	13/33/.10	11.17	137340.33	1373.40	013404



Conclusions

- We are there ! IoT & AI can improve patient safety and quality of life !
 - RF/wireless technology is easy to implement and generate lots of data.
 - Data science (AI, machine learning, analytics, etc.) has come a long way within the past decade.
 - Together they unlock applications in healthcare we never thought possible before.
- Proof?





Conclusions

- We can detect patient falls with **up to 99-100% accuracy.**
- We can detect human activities with accuracies around 95% or higher.
- We can run these algorithms in **near real time** to improve patient outcomes and quality of life related to falling incidents.
- We can even **boost** accuracy by as much as 30% for users with more challenging motion profiles !





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Thank you for listening !

- Questions? Comments?
- If you'd like to learn more about our research on using artificial intelligence/machine learning on wireless sensor and RFID/IoT applications:
 - iuysal@usf.edu
 - 813-974-8823
- Always looking for industry/academic collaborators on applications of IoT in healthcare, smart agriculture and transportation !





THANK YOU

