Deep Breathing Phase Classification with a Social Robot for Mental Health

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Deep Breathing Classification



Several social robots have been developed to support mental health wellness by encouraging users to perform deep breathing exercises, which have been shown to reduce physical signs of anxiety and stress. Deep breathing is characterized by lengthening inhales, holds, and exhales to expand the diaphragm and slow down breathing.

However, none of these robots can detect the breathing phase that the user is in. This ability would allow them to track user compliance or adjust the speed of their guidance. Detecting breathing phase is challenging because of the importance of using non-contact sensors to perform this detection, the variety of individuals that may interact with a robot, and the different interaction conditions a robot could be placed in.



In this work, we (1) collect a dataset of people performing deep breathing with a robot and (2) explore the use of modern machine learning (ML) techniques to perform deep breathing phase classification. Our results show the potential of modern ML methods to perform multimodal deep breathing phase classification using non-contact sensor input. We found that a single model can generalize between interaction conditions and individuals.

OMMDB Data Collection



- OMMDB is a novel, open-source dataset of people performing deep breathing exercises with a robot while being recorded by non-contact sensors, with ground-truth respiration data



- A data collection system was constructed, consisting of an Ommie robot, an RGB camera, an inertial measurement unit, and a respiration force belt
- Data was collected in four interaction conditions to mimic the variety of robotic

systems:

- (a) Robot not breathing, Robot on table
- (b) Robot not breathing, Robot in lap
- (c) Robot breathing, Robot on table
- (d) Robot breathing, Robot in lap
- The final dataset consists of data from 47 individuals
- Data is available at: https://scazlab.yale.edu/ommdb-dataset

Classification Methods			Results				
Per-Frame Pre-Processing	Per-Frame Features	Many-to-Many Recurrent Model	Our results show generalizat Between individuals, with 		oility:	Fold	F1
Farneback Polynomial Polynomial Junctical Flow RGB Image Optical Flow 360 x 640 x 3 180 x 320 x 2 Inertial Data 2x3	CONV. Features 1 x 50 MLP (Inertial Features 1 x 10	Sequence of Frame Features LSTM LSTM Sequence of Sequence of During			h 5-	1	0.79
			fold	Id cross-validation of uniqu		2	0.81
			 Acr Acr 	ividuals (a)		3	0.74
				oss interaction condition	ons, Jinglo	4	0.76
			inte	teraction condition (b)		5	0.81
		(3-class) 1 x 3 x 10					(a)
Min/Max norm. Motor Position				Test	Same	All	Δ
1x				Condition	F1	F1	F1
 Our learning goal was to predict deep breathing phase (inhale, exhale, or hold) from non-contact sensor input using common ML methods We utilized a Convolutional-LSTM to perform predictions due to the time-series and cyclic nature of the data 			-	Robot Breathing Table	0.84	0.81	-0.03
				Robot Not Breathing Table	0.78	0.79	+0.01
				Robot Not Breathing Lap	0.84	0.83	-0.01
			-	Robot Breathing Lap	0.80	0.76	-0.04
-							



(b)

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