Anticipating Daily Intention using On-Wrist Motion Triggered Sensing Supplementary Material

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In this supplementary material, we provide a video showing some typical experiment results, derivation of policy loss, design of reward function, quantitative results of policy network, the confusion matrix on intention classification and the detailed information of our datasets.

1. Video Example.

In this video[1], we show two typical examples of our triggered results. Motion information is consistently observed, while the policy network parsimoniously triggers the process of visual observation to reduce computation requirement. Note that we use monochrome and colored frame to represent non-triggered and triggered moment respectively.

2. Derivation of Policy Loss.

Given a set of actions A, $\pi(a \mid o_t^k; W_p)$ is a distribution parameterized by W_p over $a \in A$ to sample actions, where $o_t^k = (h_t^k, f_{m,t}^k)$ is the observation of the policy network. h_t^k and $f_{m,t}^k$ can be referred to Eq. 2 and Sec. 3.1 in the main paper respectively. $R(a)$ is the reward related to the action a. The expected reward can be expressed as

$$E_a[R(a)] = \sum_{a \in A} \pi(a \mid o_t^k; W_p) \cdot R(a) \tag{1}$$

The objective of policy gradient is to find the optimal policy (i.e., the optimal W_p) that can maximize the expected reward of a sequence of action output.

The gradient of the expectation ∇_{W_p} (referred to as ∇) can be derived as follows,

$$\begin{aligned}
\nabla E_a[R(a)] &= \nabla \sum_{a \in A} \pi(a \mid o_t^k; W_p) \cdot R(a) \\
&= \sum_{a \in A} \nabla \pi(a \mid o_t^k; W_p) \cdot R(a) \\
&= \sum_{a \in A} \pi(a \mid o_t^k; W_p) \frac{\nabla \pi(a \mid o_t^k; W_p)}{\pi(a \mid o_t^k; W_p)} \cdot R(a) \\
&= \sum_{a \in A} \pi(a \mid o_t^k; W_p) \nabla \log \pi(a \mid o_t^k; W_p) \cdot R(a) \\
&= E_a[R(a) \cdot \nabla \log \pi(a \mid o_t^k; W_p)]
\end{aligned} \tag{2}$$

By Monte Carlo sampling, the gradient equation can be approximated as

$$\nabla E_a[R(a)] \approx \frac{1}{KT} \sum_{k=1}^{K} \sum_{t=1}^{T} \nabla \log(\pi(a_t^k \mid o_t^k; W_p)) \cdot R_t^k \ , \tag{3}$$

where $\{a_t^k\}_t$ is the k^{th} sequence of triggered patterns sampled from $\pi(\cdot)$. K is the number of sequences, and T is the time when intention reached. R_t^k is the reward of the k^{th} sampled sequence at time t.

By ascending the gradient of the expected reward with respect to W_p, we can find the optimal distribution of $\pi(\cdot)$. The derivative of the policy loss, therefore, can be derived as negative gradient of expected reward. We can further derive the policy loss as

$$L^P = -\frac{1}{KT} \sum_{k=1}^{K} \sum_{t=1}^{T} \log(\pi(a_t^k \mid (h_t^k, f_{m,t}^k); W_p)) \cdot R_t^k \ , \tag{4}$$

which can be referred to Eq. 10 of the main paper.

*indicates equal contribution
[1] video url: https://youtu.be/TdHSwf_c288

Table 1. Validation on different reward setting.

observation		25%		50%		75%		100%	
R^+	R^-	Accuracy	Ratio	Accuracy	Ratio	Accuracy	Ratio	Accuracy	Ratio
10	-10	89.60%	38.02%	92.82%	39.86%	95.13%	41.33%	95.70%	42.11%
100	-100	88.77%	32.31%	93.23%	32.36%	94.88%	31.11%	95.79%	30.10%
1000	-1000	88.36%	39.22%	92.32%	42.10%	94.05%	41.95%	94.80%	40.83%

3. Design of Reward Function.

As mentioned in Sec. 4.2.1 in our main paper, we further ask a user (referred to as user A) to record multiple samples, and use them as our validation set to choose the reward setting. In Table. 1, we show that the change of the reward setting rarely affects the performance of intention prediction, while the action ratio of $R^+ = 100$ and $R^- = -100$ is much lower than others. Thus, we choose this reward setting as our final decision.

4. Quantitative Result of Policy Network

Comparison with uniform sampling policy For a fair comparison, we use a uniform sampling policy with a target trigger ratio similar to our method to train a new model. We found that uniform sampling is about 4% and 8% lower in accuracy than our method when observing 100% and 25% of the video respectively.

Analysis of triggered actions To verify the effectiveness of our triggered moment, we annotate the action of each triggered time stamp. The candidate actions are listed in the data collection stage (see Table. 3) for guiding the user to complete an intention. Note that this list may not include all the subtle actions in the video. Annotators are asked to choose the most similar action among the candidate actions or choose ”others” if they think these actions are all uncorrelated to this time stamp. The ratio of ”others” over triggered time stamps is 26% in average among three users, which contains meaningless or unlisted actions. This shows that most of our triggered time stamps contain valid information.

5. Confusion matrix on intention classification

In our dataset, an action may lead to different intentions. For example, the intentions encompassing the action ”pick up the cellphone” are ”cellphone charging”, ”talk on the cellphone”, ”use cellphone”, ”listen to music by cellphone”, and ”go outside”. The average accuracy of each of them among three users achieves 83%, 100%, 100%, 100%, 100% individually. The confusion matrix on intention classification among three users is shown in Fig. 1.

6. Hand Motion Dataset.

Inspired by [1], we select six motions. We ask eight users to collect 609 motion sequences from the right hand and one user to collect 36 motion sequences from the left hand. Table. 2 shows the number of samples of our hand motion dataset.

Figure 1. Confusion matrix on intention classification.

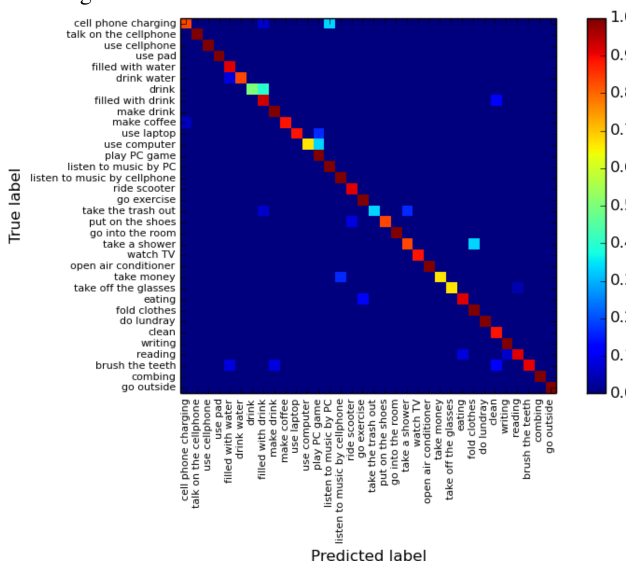

Table 2. Number of samples for each motion

Motion	# samples
training	
lift	57
pick up	55
put down	55
pull	51
stationary	112
walking	279
testing	
lift	5
pick up	5
put down	5
pull	5
stationary	10
walking	6

7. Object Interaction Classes.

We select 50[2] object categories and collect a set of 940 videos corresponding to 909 unique object instances[3]. We

[2] including a hand-free category.

[3] not counting “free” as an instance.

Table 3. Candidate actions for each intention

intention	candidate actions		
cellphone charging	pick up the cellphone	pick up the phone-charger	plug into the socket
	plug into cellphone	put down the cellphone	others
talk on the cellphone	pick up the cellphone	lift the cellphone	others
use cellphone	pick up the cellphone	keep hand steady	others
use pad	pick up the pad	keep hand steady	others
filled with water	pick up the bottle	walking	open the door
	walking	open the bottle	press the water-dispenser's button
	pick up the cup	others	
drink water	pick up the bottle	open the bottle	lift the bottle
	pick up the cup	lift the cup	others
drink	open the refrigerator	pick up the bottle	lift the bottle
	pick up the Tetra-Pak	lift the Tetra-Pak	others
filled with drink	open the refrigerator	pick up the bottle	pick up the cup
	pour the drink	others	
make drink	pick up the instant-package	pick up the cup	walking
	open the door	press the water-dispenser's button	others
make coffee	pick up the cup	put down the cup	plug into the socket
	open the coffee-machine	others	
use laptop	hold the laptop	press touch panel	type on laptop-keyboard
	others		
use computer	use mouse	type on keyboard	others
play PC game	use mouse	type on keyboard	use joystick
	others		
listen to music by PC	pick up the headphone	put on the headphone	plug into laptop
	others		
listen to music by cellphone	pick up the headphone	put on the headphone	pick up the cellphone
	plug into cellphone	others	
ride scooter	pick up the helmet	put on the helmet	pick up the keys
	open the door	others	
go exercise	pick up the towel	pick up the racket	pick up the shoes
	put on the shoes	open the door	others
take the trash out	pick up the garbage	open the door	others
put on the shoes	pick up the socks	put on the socks	pick up the shoes
	put on the shoes	others	
go into the room	pick up the keys	insert the key into the lock	wrist rotation to unlock
	open the door	others	
take a shower	pick up the towel	pick up some clothes	pick up the plastic-wash-basin
	open the door	others	
watch TV	pick up the remote-controller	sit down	lift and press the remote-controller
	pick up the bottle	others	
open air conditioner	open the door	pick up the remote-controller	lift and press the remote-controller
	others		
take money	pick up the wallet	open the wallet	take out the banknote
	others		
take off the glasses	lift arm and touch the glasses	put down the glasses	others
eating	pick up the bowl	use chopsticks	use spoons
	others		
fold clothes	pick up some clothes	fold clothes	put down clothes
	others		
do laundry	pick up laundry-basket	open the washing machine	open the detergent
	others		
clean	pick up the broom	sweep the floor	pick up the swab
	open the water tap	close the water tap	others
writing	pick up the pen-case	pick up the pen	turn on the lamp
	pick up the paper	others	

intention	candidate actions		
reading	pick up the glasses	pick up the book	open the book
	turn on the lamp	others	
brush the teeth	pick up the toothbrush	pick up the cup	open the water tap
	close the water tap	put down the cup	pick up the toothpaste
	squeeze the toothpaste	others	
combing	pick up the comb	pick up the hair-dryer	switch on the hair-dryer
	others		
go outside	pick up the backpack	put on the backpack	pick up the keys
	pick up the cellphone	pick up the bottle	open the door

collect this dataset mostly in shopping centers. Table. 4 shows all the object classes, the number of instances, and the number of frames for each category.

8. Daily Intention Dataset.

Table. 5 shows our 34 different daily human intentions. We list number of unique action sequences in each intention.

References

[1] Y. Chen and Y. Xue. A deep learning approach to human activity recognition based on single accelerometer. In *SMC*, 2015.

Table 4. Details about our object interaction dataset.

category	# of instances	# of frames	category	# of instances	# of frames
free	-	12441	towel	24	9598
cellphone	22	8466	bowl	30	7334
mouse	23	8596	chopsticks	10	5094
keyboard	16	10886	spoon	12	5781
bottle	73	16565	lamp	24	3175
hair-dryer	28	6284	headphone	23	4221
Tetra-Pak	29	11783	book	29	5696
shoes	38	6651	clothes	6	2308
cup	35	8712	pen	17	7628
instant-package	17	11727	pen-case	18	8173
coffee-machine	9	4489	water-dispenser	13	7923
wallet	13	7785	joystick	7	8161
pad	11	2890	helmet	20	6974
doorknob	3	1777	garbage	3	1899
backpack	30	8830	racket	11	6010
laptop-keyboard	15	10701	banknote	3	1877
laptop	15	6852	detergent	26	5179
glasses	23	7305	laundry-basket	9	3157
keys	16	13001	washing-machine	24	2411
toothbrush	42	5770	broom	12	6623
toothpaste	13	12401	swab	7	5618
remote-controller	7	6777	notebook	12	4389
socks	11	5207	water-tap	24	4675
phone-charger	5	3081	comb	6	3711
fridge	37	9422	washbowl	8	4204

Table 5. 34 daily human intentions.

intention	# of action sequences	intention	# of action sequences
cellphone charging	6	take the trash out	1
talk on the cellphone	1	put on the shoes	2
use cellphone	1	go into the room	2
use pad	1	take a shower	2
filled with water	4	watch TV	3
drink water	2	open air conditioner	2
drink	4	take money	1
filled with drink	5	take off the glasses	1
make drink	4	eating	4
make coffee	3	fold clothes	1
use laptop	3	do laundry	2
use computer	2	clean	3
play PC game	2	writing	5
listen to music by PC	2	reading	8
listen to music by cellphone	2	brush the teeth	11
ride scooter	4	combing	3
go exercise	3	go outside	64