CapCouch: Home Control With a Posture-Sensing Couch

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Abstract
In relaxed living room settings, using a phone to control the room can be inappropriate or cumbersome. Instead of such explicit interactions, we enable implicit control via a posture-sensing couch. Users can then, e.g., automatically turn on the reading lights when sitting down.

Author Keywords
capacitive sensors; implicit interaction; casual interaction

ACM Classification Keywords
H.5.2 [Information Interfaces and Presentation]: User Interfaces.

Introduction
Controlling devices in a smart home often requires users to start and use an app on their phone. This can be cumbersome (especially with increasing sizes of device ensembles) and puts demands on a user's attention or engagement they might not be willing or able to fulfill [9]. Instead of depending on such explicit interactions, some systems use implicit [12] or incidental [1] interaction. Here, we explore interactions with a smart living room driven by posture changes on a sensor-augmented couch. By moving interaction off the phone and into the environment less engagement is required from users [10]. Users can then, e.g., switch their TV to a fireplace scene when assuming a relaxed posture.

Related Work

Sensing posture on furniture has been explored before in several papers. Papanikolaou et al. most recently embedded pressure sensors into custom designed chairs in order to distinguish five seating postures [7]. Similarly, Mutlu et al. added pressure sensors to a standard office chair and recognized ten different postures [6]. They achieved 78% accuracy using the logistic regression classifier from WEKA [4]. Another chair was prototyped by Forlizzi et al., who focus on supporting senior users [2]. Große-Puppendahl et al. used capaticive proximity sensors in a couch [3]. They compare different classifiers for nine postures and achieved best results with radial basis function networks. Compared to their work, we use a simpler sensor setup and also explore use of postures in a concrete smart home scenario.

Figure 1: We attached six electrodes on the couch. In use, those electrodes are hidden underneath the couch cover.

Prototype

We designed our system around a *KLIPPAN* sofa from IKEA, which is designed for removable covers. We could thus embed electrodes in the space between the couch and a *Dansbo* burgundy cover. The cover hides the electrodes, but does not inhibit capacitive sensing [11]. We attached six electrodes to the couch: on both halves of the couch three electrodes are placed on the back rest, near the front edge, and towards the back (also see Figure 1). All electrodes are connected to an Arduino Uno in an RC network and each electrode's capacitance is sensed by how the RC timing changes.

We equipped the room of the couch with several smart home devices. A lamp next to the couch is plugged into a Belkin *WeMo Switch*, allowing for remote control of the lighting. Speakers and a screen enable over-the-network media playback. Sensor readings are collected on a PC which also orchestrates the connected devices.

Evaluation

Before implementing our smart home scenario, we set out to evaluate how well we could differentiate user's postures. In addition to six different seated postures, we investigated two lying down postures and also include an empty couch condition. Hence, our classes to be distinguished are:

Class 1 One person, right, on edge
Class 2 One person, right, upright
Class 3 One person, right, lean back
Class 4 One person, left, on edge
Class 5 One person, left, upright
Class 6 One person, left, lean back
Class 7 One person, lying down to right
Class 8 One person, lying down to left
Class 9 Empty couch

For each class, we recorded 100 samples (snapshots of raw capacitance sensor values while in the target posture) from 10 participants (2 female). We then analyzed the data with leave-one-subject-out cross-validation using WEKA [4]. Comparing a KNN (79.4% accuracy), a logistic regression (85.7% accuracy), and a naive Bayes (92.9% accuracy) classifier, we achieved the best results with the naive Bayes one. See Table 1 for a confusion matrix of the results when using the naive Bayes classifier.

Class	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**78.2%**	21.8%	0%	0%	0%	0%	0%	0%	0%
2	3.9%	**84.9%**	7.5%	0%	0%	0%	3.7%	0%	0%
3	0%	0.2%	**99.8%**	0%	0%	0%	0%	0%	0%
4	0%	0%	0%	**89.9%**	9.2%	0.4%	0%	0.5%	0%
5	0%	0%	0%	0.2%	**98.6%**	3%	0%	0.2%	0%
6	0%	0%	0%	0%	0%	**100%**	0%	0%	0%
7	0%	0%	0%	0%	0%	0%	**100%**	0%	0%
8	0%	0%	0%	0%	2%	0.9%	0%	**97.1%**	0%
9	0%	0%	0%	0%	0%	0%	10%	0.1%	**89.9%**

Table 1: We could recognize seating postures with an overall 92.9% accuracy using a naive Bayes classifier.

Overall, we achieve good recognition rates with a simple sensing setup. More elaborate approaches (such as in [3], where electric field sensors are used) could potentially further increase accuracy. We also only used a small number of electrodes ([6], e.g., ran some tests with 2048 sensors on a smaller chair). Increasing the number of sensor locations on the couch could allow for even higher accuracy or distinguishing a larger set of postures (such as postures of multiple users). For our purposes though, the classification was good enough to prototype our envisioned smart home scenario.

Controlling Devices via Postures

We used our couch and device ensemble to prototype a smart living room scenario. In this scenario, the system has been trained by observing how a user usually behaves when on his couch. Now, when he comes home and sits down on the couch, the lamp next to the couch switches on and the display shows a welcome message. The user scoots back, sitting more comfortably, and starts checking his phone. The couch detects this posture change and the system starts to play some music. Once done with his phone, he leans back on the couch, assuming a relaxed position to watch some TV. This is also picked up by the couch, which triggers the system to suspend music playback and switch the screen to display of broadcast TV (this is shown in Figure 2). As time passes, the user grows tired and decides to lay down on the couch. This triggers the lights to switch off and the TV to stop running. Instead, a fireplace scene is displayed to further facilitate a relaxing atmosphere. Of course, the system could also be programmed to push users to move to the bedroom once such posture is detected.

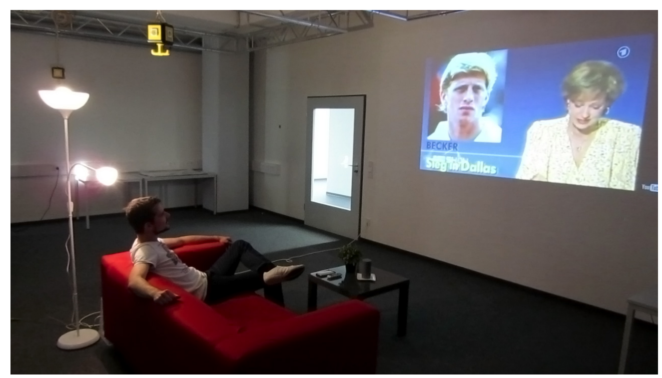

Figure 2: Users can control lighting and media in a smart living room by adjusting their posture on the couch.

Conclusion

We have presented a posture sensing couch (using a simple and cheap setup) that enables implicit control of a smart living room. Note that users still retain the power to override the system. They can, e.g., use the remote to change channels or switch off the TV. However, posture-sensitive furniture, such as our couch, can play a role in supporting users' everyday behavior. They enable a low-engagement channel for interaction, while not prohibiting users from taking back control via devices such as their phone. The implicit behavior can either be pre-programmed, defined by the user, or trained based on users' behavior. Such provision of a low-engagement side-channel for interaction in a smart-home context is similar to recent work on low-effort user recognition [8].

An open question with systems such as the CapCouch is how to make sure implicit behavior is not annoying for users. Users, e.g., will not always want the lamp next to the couch to switch on when they sit down. One approach would be to add more kinds of sensors to be able to reason better on the user's intent. However, this is likely to still fail sometimes and remain annoying for users. Instead, we envision future versions of capacitive sensing furniture to be much higher resolution (either uniform or on more critical parts such as the armrest). Users can then use more intricate gestures for control and a larger set of postures could be available (increasing the entropy of any specific posture). Embedding feedback into the couch (like EmotoCouch [5]) could also support interaction.

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