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Sensing Individual Topic Review

B05 - Contactless Sleep Apnea Detection

Nandakumar et al. set out with their experimental ApneaApp to replace expensive and invasive PSG (polysomnography) tests on patients with potential apneas with simply a smartphone on their bedside. They believed they could detect central apneas, hypopneas and obstructive apneas by sending out high frequency (18-20 kHz) sound pings from the smartphone's speaker and recording the reflections of those waves off of the patient's body with the microphone. Specifically, they wanted to do so by detecting chest movements - cessation in amplitude for central apneas, 30% of typical amplitude for hypopneas, and increased amplitude for obstructive apneas. To achieve this they altered traditional FMCW waveform processing to allow for detection of the minute frequencies that chest breathing movement range in. This allowed them to use an Android phone to detect apnea events on a variety of patients to practically the same accuracy as the concurrently performed PSG.

B09 - BodyBeat: A Mobile System for Sensing Non-Speech Body Sounds

Through BodyBeat, Rahman et al. wanted to create a highly mobile system for sensing non-speech body sounds. With simply a customized piezoelectric microphone with an onboard ARM system worn on the body and paired with an Android smartphone, they believed they could outclass current body sound sensing techniques at a cheaper price. They found the neck was the best position for capturing as wide of a range of body sounds as possible, and that from there the ARM system could detect frequency frames and send them to the smartphone. In the smartphone app, sound classification using SVM and other techniques was conducted with a heavily reduced and optimized feature set to keep CPU usage under 12% and processing time short. They found that BodyBeat indeed performed much better than current systems for body sound detection.

B19 - CNN-based Sensor Fusion Techniques for Multimodal Human Activity Recognition

Münzer et al. investigate the ability of convolutional neural networks (CNNs) to optimize human activity recognition (HAR) for applications such as physical health promotion. They particularly examine these aspects of deep learning and any improvements they bring to HAR: data specific normalization, fusion of multimodal data, and robustness with currently available training data. Their results strongly suggest that data normalization techniques be required, and they also introduce a pioneering pressure-specific method for normalization. They also find that late fusion of data combined with a shared filter approach heavily optimize detection accuracy and reduce the CNN's dependency on available training data.

B4 - Towards Wearable Cognitive Assistance

Ha et al. envision a rapidly approaching future where highly performing and minimalistic wearable devices can be paired with offloaded computing power in the cloud to guide cognitively impaired or deteriorating patients through daily activities. They emphasize the importance of unobtrusiveness, situational awareness and low latency for such a device, and implement a proof-of-concept named Gabriel. Gabriel is built on a Google Glass and utilizes a custom server cluster as a "cloudlet" for offloading computing. Ha et al. highly stress the importance of local network cloudlets as an intermediate step to cloud servers, to be able to use their power while not suffering the high latency of accessing these servers via the Internet. The initial tests of Gabriel in required tasks such as facial recognition and activity detection show that while the Glass combined with the cloudlet has the right computing power, the thermal issues of the Glass as well as the unacceptably short battery life means that there is much more room for improvement in our mobile devices before Gabriel becomes reality.