WARD: A Wearable Action Recognition Database

Allen Y. Yang
Department of EECS
University of California
Berkeley, CA 94720 USA
yang@eecs.berkeley.edu

Philip Kuryloski
Department of ECE
Cornell University
Ithaca, NY 14853 USA
pjk25@cornell.edu

Ruzena Bajcsy
Department of EECS
University of California
Berkeley, CA 94720 USA
bajscy@eecs.berkeley.edu

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Abstract

In this paper, we present a public human action database called WARD (wearable action recognition database). The database consists of continuous sequences of human actions measured by a network of wearable motion sensors. The wireless sensors are instrumented at five body locations: two wrists, the waist, and two ankles. Each custom-built sensor carries a triaxial accelerometer and a biaxial gyroscope. There are 20 human subjects in the database: 13 male and 7 female. The current version of WARD includes a rich set of 13 action categories that covers some of the most common actions in a human's daily activities, such as standing, sitting, walking, and jumping. It serves as a benchmark to compare the performance of existing wearable action recognition algorithms. Using WARD, we compare two action-recognition algorithms: nearest-neighbor (NN) and distributed sparsity classifier (DSC). Guided by the state-of-the-art performance, we discuss future directions in high-quality human action databases and distributed recognition techniques.

Keywords

Body Sensor Networks, Wearable Action Recognition, WARD, DexterNet

ACM Classification Keywords

H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

Wearable Action Recognition Database

Body sensor networks allow us to instrument the body with various sensor types and capture a wide variety of data in real-time. This creates the potential for a seamless link between the actions and state of an individual and a computer or information system they wish to interact with. Furthermore, the body sensor network has the potential to conform to wearer to provide an intuitive and natural interface. In this paper, we consider the problem of human action recognition via wearable motion sensor networks. Particularly, we present a public human action database called WARD (wearable action recognition database) [3]. The database can be downloaded at: http://www.eecs.berkeley.edu/~yang/software/WAR/.

The design of WARD is based on the following principles:

1. The database contains sufficient numbers of human subjects with a large range of age differences.
2. The action classes are general enough to cover most typical activities in a human's daily life.
3. The locations of the wearable sensors are selected to be practical for full-fledged commercial systems
4. The sampled action data contain sufficient variation, measurement noise, and outliers in order for existing and future algorithms to meaningfully examine and compare their performance.

The current version of WARD is collected over a period of two weeks on 20 human subjects (7 female and 13 male). It includes the following 13 continuous-action categories: 1. Stand. 2. Sit. 3. Lie down. 4. Walk forward. 5. Walk left-circle. 6. Walk right-circle. 7. Turn left. 8. Turn right. 9. Go upstairs. 10. Go downstairs. 11. Jog. 12. Jump. 13. Push wheelchair. Each subject is asked to perform five trials for one action category.

The human actions are measured using a network of five motion sensors instrumented on the body: two wrists, the waist, and two ankles. A wireless sensor system is utilized in conducting the experiment, which is called DexterNet [2] (see Section 2). The sensor data have been converted and saved in the MATLAB environment. The database also includes a MATLAB program to visualize the action data from the motion sensors. For more details about the data collection, please refer to the human subject protocol included in the WARD database.

DexterNet

DexterNet is an open, hierarchical sensor platform for heterogeneous body sensor networks (shown in Figure 1). It supports real-time, persistent human monitoring in both indoor and outdoor environments. DexterNet adopts a 3-layer architecture consisting of the Body Sensing Layer (BSL), Personal Network Layer (PNL), and Global Network Layer (GNL). The BSL and PNL layers are driven by an open-source software framework called SPINE (Signal Processing in Node Environment) [1]. SPINE supports dynamic, over-theair discovery and configuration of a heterogeneous network of sensor equipped motes, as well as a library of signal processing functions available on each node. It has also been designed to allow the convenient introduction of support for additional sensors and processing functionality as needed.

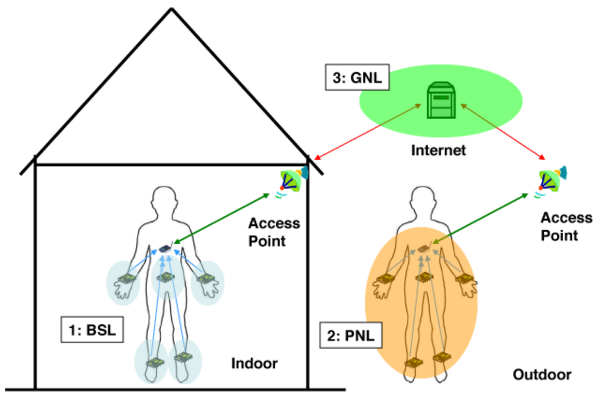

Fig. 1. The three-layer architecture of DexterNet: 1. Body sensor layer (BSL). 2. Personal network layer (PNL). 3. Global network layer (GNL). The pivotal component of the system is a Nokia N800 Internet tablet at the PNL as a mobile base station that communicates both to the BSL via IEEE 802.15.4 and the GNL via other broadband wireless channels.

Each custom-built motion sensor used in the experiment has a triaxial accelerometer and a biaxial gyroscope, which is attached to a standard TelosB network sensor. Each sensor axis is reported as a 12bit value to the node, indicating values in the range of +/- 2g and +/- 500°/s for the accelerometer and gyroscope, respectively.

The current hardware design of the motion sensors contributes certain amounts of measurement error. The accelerometers typically require some calibration in the form of a linear correction, as sensor output under 1g may be shifted up to 15% in some sensors. It is also worth noting that the gyroscopes produce an indication of rotation under straight line motions. These systematic errors appear to be consistent across experiments for a given sensor board.

Wearable Action Recognition

Inspired by compressive sensing theory, we have proposed a distributed action recognition algorithm called distributed sparsity classifier (DSC) [3]. The new algorithm emphasizes the following advantages of a distributed recognition system on sensor networks over the traditional centralized recognition systems:

1. Good decisions about the validity of local measurement on the nodes can reduce the communication between the nodes and the server, and hence reduce the power consumption for communication.

2. The ability for the sensor nodes to make biased local decisions also makes the design of a global classifier more flexible.

3. From a more general perspective beyond action recognition, the ability for individual sensors to make local decisions can be used as feedback to support certain level of autonomous actions to local events without the intervention of a central system.

The DSC algorithm is operated in a distributed fashion on individual sensor nodes and a base station computer. We model the distribution of multiple action classes as a mixture subspace models, one subspace for each action class. Given a new test sample, we seek the sparsest linear representation of the sample w.r.t. all training examples. We show that the dominant coefficients in the representation only correspond to the action class of the test sample, and hence its membership is encoded in the sparse representation. One can also choose to activate a subset of the sensor nodes on-the-fly due to sensor failure or network congestion. The global classifier is able to adaptively modify the optimization process and improve the overall classification upon available local decisions.

We has compared the performance of DSC with another popular method, namely, nearest-neighbor (NN) based on WARD. The experiment shows that DSC compares favorably to NN in the 13 action categories, and achieves the state-of-the-art performance. We have further showed that the recognition precision of DSC decreases gracefully using smaller subsets of active sensors. This validates the robustness of the distributed recognition framework on an unreliable wireless network, while most centralized algorithms such as NN and decision trees have to retrain their classification parameters whenever the configuration of the sensor networks changes.

Conclusion and Future Directions

One important observation is the choice of sensor locations in WARD. Motion measurements from the ankle locations tend to provide less information than other conventional locations such as the knees and the waist to discriminate certain categories of upper-body motions and even some lower-body motions (i.e., between standing and sitting). We have suggested in [3] to replace the ankle locations with other locations around the knees or thighs in order to improve the classification.

Another limitation in the current system and most other body sensor systems is that the wearable sensors need to be firmly positioned at the designated locations. However, a more practical system/algorithm should tolerate certain degrees of shift without sacrificing the accuracy. In this case, the variation of the measurement for different action classes would increase substantially.

Finally, an important consideration in the deployment of wireless body sensor networks is the need to protect the wearer's privacy. Work on private-key and public-key cryptography schemes for sensor networks is applicable, but must be integrated into an appropriate authentication and authorization framework. To the end, we outline the following three security challenges for resource-constrained body sensor networks for future research: 1. User authentication. 2. Data encryption. 3. Communication congestion.

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References

[1] SPINE http://spine.tilab.com.

[2] P. Kuryloski, A. Giani, R. Giannantonio, K. Gilani, R. Gravina, V-P. Seppa, E. Seto, V. Shia, C. Wang, P. Yan, A. Yang, J. Hyttinen, S. Sastry, S. Wicker, and Ruzena Bajcsy. "DexterNet: An Open Platform for Heterogeneous Body Sensor Networks and Its Applications." Submitted to ACM International Conference on Information Processing in Sensor Networks (IPSN), 2009.

[3] A. Yang, R. Jafari, S. Sastry, and R. Bajcsy. "Distributed Recognition of Human Actions Using Wearable Motion Sensor Networks." Submitted to the Journal of Ambient Intelligence and Smart Environments, 2008.