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References:

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6386882/>

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4241367/>

<https://www.cdc.gov/physicalactivity/worksite-pa/index.htm>

<https://www.who.int/news-room/fact-sheets/detail/physical-activity>

Physical activity classification in free-living conditions using smartphone

accelerometer data and exploration of predicted results

The healthcare benefits associated with regular physical activity monitoring and recognition has been considered in several research studies. Solid evidence shows that regular monitoring and recognition of physical activity can potentially assist to manage and reduce the risk of many diseases such as obesity, cardiovascular and diabetes.

Along with President Bush, I believe that physical activity should be an essential component of any comprehensive disease prevention and health promotion strategy for Americans. We know that sedentary behavior contributes to a host of chronic diseases, and regular physical activity is an important component of an overall healthy lifestyle. There is strong evidence that physically active people have better health-related physical fitness and are at lower risk of developing many disabling medical conditions than inactive people

P1:

statistics showing

* Globally, 1 in 4 adults is not active enough.
* More than 80% of the world's adolescent population is insufficiently physically active.

Impacts of insufficient physical activity → chronic **diseases -->** the social and economy negative impacts/ The social and economic point of view will be impacted by the care and assistance needs as a result of the trend of rapid growth in the number of persons with physical disabilities.

P2: How technologies help ?

Solid evidence shows that regular monitoring and recognition of physical activity can potentially assist to manage/ encourage

an intelligent activity recognition system can also detect when the older adults are passive and can recommend that they move around, take a walk, etc. This can be done using various senses similar to the ones humans have. Some solutions are based on computer vision [[2](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6386882/#B2-sensors-19-00458)], while other works have been based on audio recognition techniques [[3](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6386882/#B3-sensors-19-00458)] (rather a complementary addition to already existing methods) or radio frequency identification (RFIDs) [[4](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6386882/#B4-sensors-19-00458),[5](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6386882/#B5-sensors-19-00458),[6](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6386882/#B6-sensors-19-00458)]. Another sense suitable for human activity recognition is motion, recorded through different sensors.

 innovative ICT-enabled assisted living or “ambient assisted living” (AAL). The main scope of such solutions is to apply the ambient intelligence (AmI) concept and technologies to help people live longer in their natural environment.

P3: (motivations)

Technologies to track human physical activity: vision, wearable sensors → talk about their limitation

Then highlight why use hp?

→ Since we believe that various types of human-carried sensors might discourage older adults from participating in an activity recognition-based system, we focus on one sensor-based ubiquitous piece of technology, namely smartphones, which are far more than just communication devices. They are packed with high-end hardware and features for every type of user. Additionally, a large number of sensors can be found inside them, including motion sensors. Therefore, this paper studies human activity recognition and how it can be achieved using the sensors available on a smartphone.

(very good reference: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6386882/>)

New sub-section: The related works: smartphones used for HAR, approaches applied on HAR

New sub-section: contributions of the work ( 3 points)

Eg:

This paper is inspired by the hierarchical representation learning in DNNs. The three contributions are as follows. 1) An RR-based S-DNN, i.e., deep analytic network (DAN) and its kernelization (K-DAN), are outlined to learn a non-BP S-DNN involving no GPU, no enormous training set, and no elusive hyper-parameter tuning. 2) DAN/K-DAN are attested triggering feature relearning from the pre-extracted baseline features and the structured features, of which CNNs and RNNs are impracticable. Under a certain condition that the relearned feature dimension is outnumbered by that of original, DAN/K-DAN perform also feature compression. This is overlooked and thus not being explored thoroughly in other relevant works. 3) DAN/K-DAN are analyzed for proofs contributing to the improved generalizability. We portray the basic self-learnable unit to assemble the deep DAN/K-DAN construction in Fig. 2, and the complete DAN/K-DAN pipeline is illustrated in Fig. 3.

Eg:

We summarize our main contributions of this work into fourfold:

1)

We evaluate the RCM and RLTCM performance using the orthogonal transforms of different properties as filter banks. More specifically, we opt for Identity Transform (IT), Discrete [Haar Transform](https://www.sciencedirect.com/topics/computer-science/haar-transform) (DHT), Discrete Cosine Transform (DCT) and Karhunen-Loève Transform (KLT) in this work.

2)

We devise basis selection schemes for each filter bank construction to gain control over the extracted feature dimension.

3)

We present a more comprehensive study on RLTCM with the introduction of patch-wise normalization, on top of our previous work [[21]](https://www.sciencedirect.com/science/article/pii/S1047320318301639#b0105).

4)

We also provide extensive experimental analysis and discussion using relatively more face datasets, including the unconstrained LFW for the face verification task. We demonstrate that a simple RLTCM manages to outperform state-of-the-arts face descriptors.

New section: the proposed solution

Nex section: experimental results

* Different classifiers
* Additional experiments: influence of parameters
* Comparison with other techniques
* Classifiers:

--> 2 Confusion matrices (activity) with SVM classifier

→ comparison with different classifiers for db1 and db2: logistic regression, svm, rf, naive bayes, knn-manhattan, knn-euclidean

       → measure: precision, recall, f1-score