GERÇEK-ZAMANLI HAREKET TAKİBİ

REAL-TIME ACTIVITY MONITORING

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Özet

Son yıllarda, kişilerin günlük yaşam aktivitelerini uzaktan ve özel hayata müdahale etmeden tanıyan aktive takip sistemlerine (ATS) ihtiyaç artmıştır. Özellikle kişilerin ev ortamında bakımını gerektiren durumlarda bu sistemlerden faydalanılmaktadır. Giyilebilir sensör ve sensör haberleşme teknolojilerinin gelişmiş olması da bu tür sistemlerin fizibilitesini artırmıştır. Kullandığımız veri toplama ve sınıflandırma modeli, basit ve bileşik hareketleri gerçek zamanlı olarak tespit etmekte, günlük hayata müdahale etmeyen bir çözüm sunmak için verileri tek bir 3B ivmeölçer ile toplamaktadır. Çalışmanın mevcut aşamasında yöntemimizi, elin baskın olduğu basit hareketler olan **yemek yeme***(eating)*, **silkeleme/dökme** (*pouring*), **içme***(drinking)*, **diş fırçalama** (*toothBrushing*) ve **anahtar çevirme***(turningKey)* aktivitelerinden oluşan veri kümesi üzerinde literatürde ağırlıklı kullanılan bilgisayar tarafından üretilmiş yapay verilerle değil, gerçek test ortamında insan deneklerle yapılmış testlerle kısmen doğruladık. Seçtiğimiz aktivitelerin, birbirine oldukça benzer sinyal örüntüleri ürettiği halde, gerçek zamanda ayırt edilebildiğini gösterdik. Önerdiğimiz yöntemin gücü ve yeniliği, yöntemimizin, hareketler arası geçişlerin (transitions) sinyal örüntülerini veritabanında tutmayı gerektirmemesinden ve bu geçişlerin tespitine tahsis edilmiş bir algoritma çalıştırmamasından dolayı literatürde önerilen çalışmalara göre daha hızlı olmasından kaynaklanmaktadır. Farklı denekler üzerinde yaptığımız testlerde elde ettiğimiz sonuçlar oldukça umut vericidir.

Real Time Continuous Activity Monitoring Model (RT-CAM)

Figure 1 illustrates the system architecture of RT-CAM. Operation of RT-CAM is initiated by sensor transmitting continuous activity signal, which is composed of *cs* segments, to the DA (Data acquisition) unit. Each segment, lasting for the period *t,* is forwarded from DA unit to SAD (Simple action detection) module. Then, the segment is processed by SAD for being labelled as one of the simple actions (SA) in the action set after knowledge extraction process is applied.

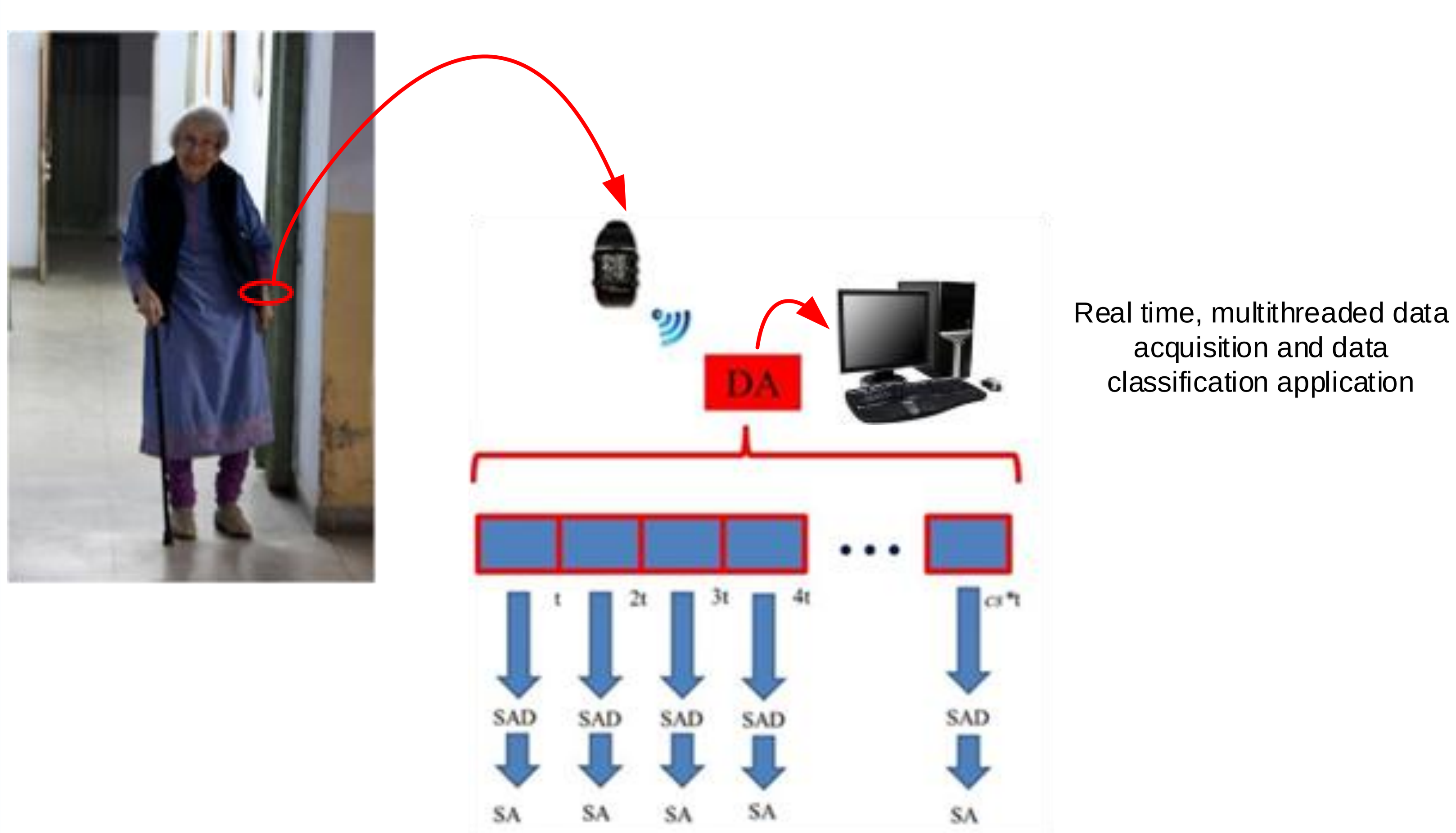


Figure 1. System architecture of RT-CAM

Being an adaptation of SVM, RT-CAM$_{KD}$ (knowledge discovery module of RT-CAM) performs feature extraction phase and most of the classification phase at once. Unlike SVM, RT-CAM$_{KD}$ can differentiate between multiple classes, comparing the similarity between actual classes and the psudo action introduced, which is the reference action. As the segmentation policy to partition continuous real time data stream, RT-CAM$_{KD}$ follows explicit segmentation where each segment corresponds to either a simple action or a transition.

The proposed method, which is formed as an SVM adaptation, differs from the SVM in the following aspects:

- SVM is a binary classifier, which means only two classes can be differentiated using SVM. RT-CAM$_{KD}$ approaches differently to the multi-class problem which is multi-activity differentiation in our context. RT-CAM$_{KD}$ introduces the notion of *reference action* and assigns the reference action to be a pseudo class to form a basis of comparison between the actual classes. An error value, which is the measure of the difference between the training and test data, is calculated. Then, the action yielding the smallest error value is assigned to be the detected action.
- SVM tries to find a seperating hyperplane between two classes to be differentiated and the type of the test data is determined considering which side of the hyperplane the test data lie whereas RT-CAM$_{KD}$ avoids seperating hyperplane calculation. By doing that, the operation of solving systems of equations carried out in SVM is replaced by the operation of multiplying a matrix by a vector in RT-CAM$_{KD}$ where inverse matrix calculation, which is necessary for solving systems of equations, is eliminated.
- SVM maps the data to a new space using proper Kernel functions if the data are not linearly seperable so that a seperating hyperplane can be found in the new space. Though RT-CAM$_{KD}$ eliminates the seperating hyperplane calculation, a Kernel function is still used because we used the same Kernel function in our preliminary study of this work which is accepted as a publication [1] and we obtained successful results and we went on using the Kernel function.

Contribution

We develop a non-invasive solution which we call RT-CAM, pursuing real time continuous monitoring of hand oriented activities. A preliminary study of this work is accepted as a publication [1]. RT-CAM does not require generating combinations of features and carries out transition detection without being trained with patterns of transitions. RT-CAM is evaluated regarding the following criteria:

- Intra-person and inter-person classification accuracy
- Successful recognition rate of simple actions
- Successful recognition rate of composite actions as a whole
- Real time delay

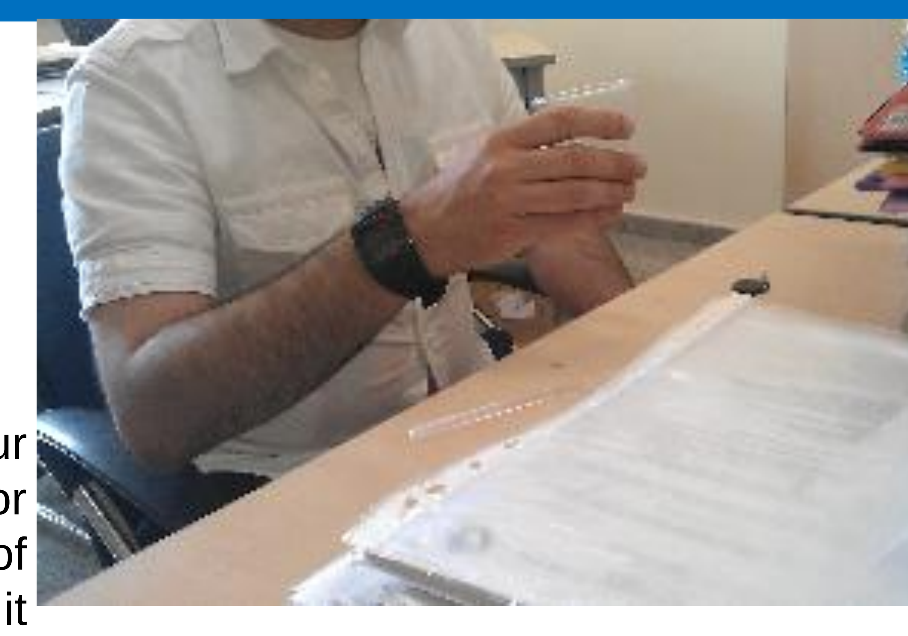
According to our findings, our model RT-CAM is promising for real time continuous monitoring of hand oriented activities. Also, it does not necessitate large number of subjects who should provide training data. With regard to the features of RT-CAM mentioned, the contribution of the thesis can be summarized as follows:

- Designing a tool which can detect transitions
- Recognizing hand based activities with high detection rates
- Distinguishing the selected activities in real time though they are similar to each other

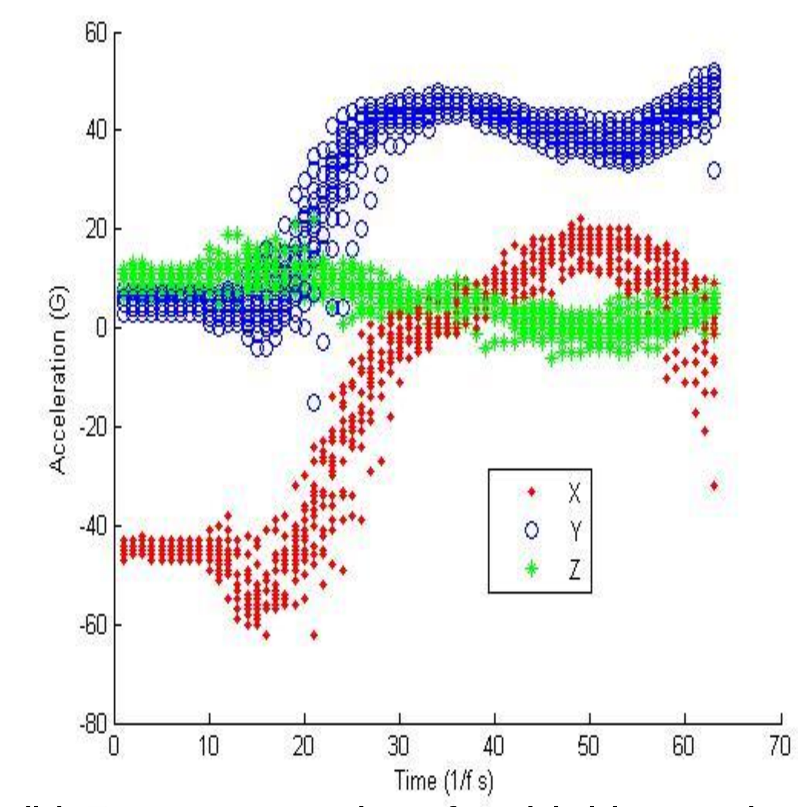
Experimental setup

The raw sensor data are composed of X, Y and Z axis acceleration values acquired from the 3D accelerometer built in TI Chronos eZ-430, which wirelessly communicates with the USB access point connected to the PC. Figure 2 shows the raw sensor data and training output generated for drinking activity. The testbed overview is explained in Figure 3.

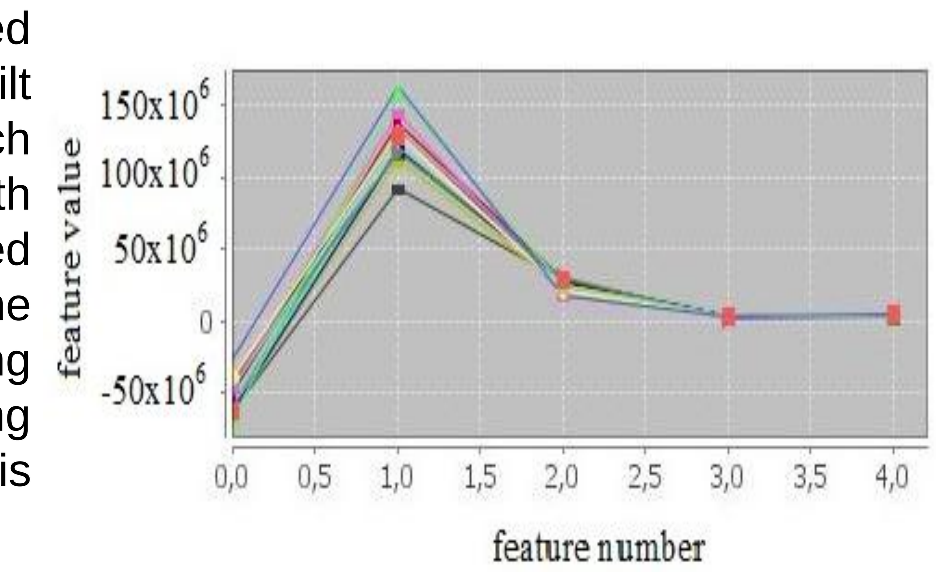
Figure 3. Testbed overiew



(a) The human subject performs drinking action



(b) Raw sensor data for drinking action



(c) Training output for drinking action

Figure 2. Processing of drinking activity data

Potential application areas and future work

Running activity detection algorithm on smart phones (Figure 4) can open up a wide variety of responses generated upon activity detection. Also, creating a wireless network of different type of sensors can increase the successful detection rate of the activities we studied. Also, data loss introduced by data communication should be analyzed in terms of effecting detection accuracy.

Results

We carried out experiments on 4 different subjects and present our best achieved results. Intra-person test results are the following: *ToothBrush, drink, drink_toothBrush*, *toothBrush_drink* and *toothBrush_pour* are recognized with 100% accuracy. *Drink_toothBrush_pour* and *toothBrush_drink_pour_turnKey* are detected with 80% and 70% accuracy respectively. Inter-person test results are the following: *ToothBrush*, *drink* and *pour* are detected with 100% accuracy. *Drink_toothBrush*, *drink_toothBrush_pour* and *drink_toothBrush_turnKey* are recognized with 80% accuracy. Real time overhead introduced by RT-CAM is 0.055 seconds, which is better than best achieved result in the literature. Considering all these features, RT-CAM is an applicable solution in real time continuous activity monitoring.

Figure 4. Activity detection algorithm runs on a smart phone, communicating with a heterogeneous wireless sensor network

References

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2. Aiello, F., F. L. Bellifemine, G. Fortino, S. Galzarano and R. Gravina, "An Agent-Based Signal Processing In-node Environment for Real-Time Human Activity Monitoring Based on Wireless Body Sensor Networks", *Engineering Applications of Artificial Intelligence*, Vol. 24, pp. 1147-1161, 2011.