Wearable Computing

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ABSTRACT

Wearable computing means computers that extend our body, offering useful information. Wearable computing is used in various industries nowadays. Wearable computing system can be an electronic device embedded into fiber which turned into clothes, small electronic device such as iPod Nano that is worn by a user as a wrist watch or body-worn sensors that recognize activities. In wearable computing, human constantly interacting with computer. Smart phones are considered to be a wearable computer, video games that use wearable sensors are being researched and developed and also in robotics, activity recognition, which is achieved by the wearable computer, plays major role. Body-worn sensors are used to recognize human activity to collect data set to train human-like robots as well as improving robustness of robots by sharing of activity recognition systems between platforms or domains. Sharing the activity recognition systems enables the sensors can be replaced or upgraded or a robot can learn activities from the other robot. However, for accurate data set to be produced, the modality of the sensor used is very important and take into account that a situation like sensor moves from its original position while collecting date. All these factors have to be put into the consideration when developing a wearable computer to produce high quality product.

Author Keywords

Wearable computing; Sensors; Context-aware; Activity recognition

INTRODUCTION

When the computer was first invented, it was enormous that nobody thought of carrying it around and it was very slow, took overnight to calculate or do certain tasks, then the speed of computation increased exponentially and also the size of the computer got smaller that it can be carried around such as laptops, tablet PC. The size became so small that it is wearable. Smart phones and MP3 players are considered to be the wearable computers.

Wearable computer means small electric device that is integrated into clothes or wear it under or on top of clothes.

The use of wearable computing is increasingly and spreading very fast across many different areas. In sports it is used to train athletes to help them to improve the performance by useful tips and feedback. In the industrial area, trains trainees so that the supervisors do not always have to be around all the time [3], and also to train robots [5]. Research is going on with game using on-body sensors.

Activity recognition plays very important role in wearable computing as it provides information used in context-aware application [3].

Sensor choice is really crucial. Even if sensor is good, output performance can be degraded as the sensor can be displaced during the operation. There are several approaches to improve the data.

This report will look into the challenges in achieving wearable computing: how the activity recognition system is shared between different domains and platforms, how the number of sensors and contexts influence the output performance of the system and could the results be improved despite the displacement of sensors during the operation. Where these technologies are used in real life application tested.

CHALLENGES

Activity Recognition

Activity recognition is one of the fundamental keys in the wearable computing [5]. Correctly capturing and analyzing human motion

The activities and manipulative gestures of a user are an important aspect of the context. The recognition of activities and gestures from body-worn sensors may be applied

Sharing activity recognition between platforms

Many studies regarding the wearable computing are about finding out the methods to improving the performance and robustness of the human activity recognition system.

Sensors

In wearable computing, using the most suitable sensor is important as it can change the final results, affects the performance or the overall cost of the system. It is not only important what kind of sensors are used in a particular wearable system but also have to take into consideration that the sensor could move or break, giving incorrect output. To increase the robustness of the system, sensors have to be interchangeable. Kunze et al. conducted an experiment to explore the options to whether substituting the gyroscope sensors with the magnetic field sensors is possible and what is the costs and benefits of doing it [can].

With the activity recognition system in wearable computing, an assumption is made that the on-body sensors will stay in the same position while the data set is gathered. In reality, this is highly unlikely to be happened because the operation of gathering data set could be separated into several sessions and during that time the sensors could not be in the same place as before. An example is a person might take the body-worn sensors off and put it back on between the operations. The displacement of sensors can affect the output and eventually the final results.

For accurate activity recognition, number of different sensors has to be distributed over the body but it is very complex process and many researches were involved studying the classifier using the dataset of different sensors.

APPROACHES

Method of sharing and re-using the activity recognition system between different platforms or domains was studied by Roggen et al. [5]. Conducting activity recognition naturally leads to human robot interaction. Also they focus the use of activity recognition system in

[2] investigates the possibility and method of replacing gyroscope with magnetic field sensor. Gyroscopes only provide information about angular velocity and it is widely used where accurate information about rotational movement is required. If magnetic field sensor can correctly derive the angular velocity then it will cost, size and energy saving to the wearable systems. Angular velocity can be calculated using the values of 3D magnetic field assumes that the magnetic sensor provides data in a standard basis coordinate system. Also the accurateness of the value is depends on what type of movement is performed and environmental factor such as magnetic disturbances caused by electrical devices and metallic objects.

Bayati et al. [1] investigated how sensor displacement could effect the overall feature distribution and developed the methods to provide online unsupervised adaptation in classifier in acceleration based activity recognition to estimate the shifts in the feature distributions and adapt the classifier. This approach will help the classifier to calibrates itself and become robust against the position of sensor being moved while the operation. The assumptions were made that the other than the movement of sensors, everything remains the same and another assumption is the shift of an unknown magnitude and direction can characterize the change in the feature distribution.

METHODOLOGY AND FINDINGS

These methods can be used in various areas, sports or for training automobiles.

[2] Performed experiment on 15 different users for nearly 20 hour, the activities ranging from having breakfast, video gaming, homemaking, bicycle repair, car inspection to gym exercising which involves using various body part. For the signal level evaluation, the sampling rate was 50 or 100 Hz. The results show that there are three distinct groups that have similar output. This is because the similarity of movement of the body, error rate below 20% and very few above 40%. In the implications on context recognition, the dataset of gym exercise was used and the performance of magnetic sensors was only about 10% to 15% worse than gyroscope and improvement in compensating sensor shifts. In most of cases the magnetic field sensors provided very close values to the angular velocity the gyroscope provided.

[1] used an online version of the Expectation-Maximization algorithm to estimate the shift of the distribution and original classifier classifies the shifted back incoming samples that has been. The algorithm was tested on three different datasets: Synthetic dataset, HCI gesture dataset and fitness activity dataset. For synthetic dataset, 100 repetitions of the simulation on both fixed and adaptive Linear and Quadratic Discriminant Analysis (LDA and QDA) classifiers were conducted. The results of classifiers used fixed mechanism were highly biased and in accurate whereas adaptive classifier was able to prevent the bias and was highly accurate. HCI gesture dataset, five different hand gestures: an upside-down triangle, an infinity symbols, namely a triangle, a square and a circle, were repeated 50 times each. With the same sensor, the adaptive LDA (aLDA) performed better than aNCC. For the fitness activity dataset that involved five different aerobic movements of the leg, and the results shows that an increase in performance in aLDA compared to fixed LDA was only detected when the change of movement was large. Even though the experiment was carried out using accelerometers, other sensors can also be used in the adaptive classifier. This work can be applied in practical applications where wearable sensor is required like gaming, industrial maintenance and health monitoring to enhance their performance.

[6] performed similar experiment as [1] where this involves improving the performance by detecting anomalous nodes, degraded or altered sensor behavior, in and change to correct, expected values. Two main steps are required to resolve the anomalies in the network. The first step is to identify the anomalous and the second step is to replace it with correct value. Also there are two possible methods to the replacing the value, removing form the classification chain and replacing it to other values. The replacing practice can be done either at the signal level, feature level or classification level. The results show as the number of noisy sensor increased the accuracy decreased and low level of noise was not well detected and this is not significant as it will not degrade classification performance anyway. For different conditions were compared: ‘No Removal’, no anomalies detected, ‘Automatic Removal’ removing anomalous classifiers from the fusion, ‘Perfect Removal’, the classifier with anomalies is known and it is removed from the chain and real world scenario where everything is unknown and not predicted. The final results illustrates the system performance can be improved using detection and compensation process online.

Lei et al. [3] conducted the experiment on dynamic sensor fusion to increase the resources and performance of sensors. To collect the motion information, they used the Shimmer wireless sensor platform, which is a perfect for wearable applications as it is a small sensor platform and suitable for monitoring the human movements and also determining body sensor networks. For fusion of activity recognition,

CONCLUSION

Electronic devices surround our lives; it will not be the same without them. Recognition of human motion is very difficult as the mapping of sensor signals to activity classes is varied [5]. Each level of the activity recognition system is essential, as the system will not operate correctly. Making the activity recognition system sharable is very large step towards the making of more stable, robust and maximized performance system. There are many studies in wearable computing involves using activity recognition sharing classifier level [1], [2], [3], [4], [6]. Choosing the right sensors for the system also leads to the better system performance and saving energy as well as cost [2]. [2] conducted whether replacing the gyroscope with the magnetic field sensor to obtain the angular velocity is achievable by sharing the classifier and it will be possible to replace other sensors.

FUTURE WORK

As wearable, mobile or ambient computing is becoming more attractive to people in real world and starting to integrate this technology to the real world situation such as gaming industry, medical, automotive production industry [4]. People are making the best effort to develop better system. With replacement if sensors, [2] authors are investigating to see if more accurate angular velocity is achievable by combining magnetic field sensor with an accelerometer.

REFERENCES

1. Bayati, H., del R Millan, J. and Chavarriaga, R. Unsupervised Adaptation to On-body Sensor Displacement in Acceleration-Based Activity Recognition. In *Wearable Computers (ISWC)*, 2011 15th Annual International Symposium on. (2011), 71-78.
2. Kunze, K., Bahle, G., Lukowicz, P. and Partridge, K. Can magnetic field sensors replace gyroscopes in wearable sensing applications? In *Wearable Computers (ISWC)*, 2010 International Symposium on. (2010), 1-4.
3. Lei, G., Bourke, A.K. and Nelson, J. An efficient sensing approach using dynamic multi-sensor collaboration for activity recognition. In *Distributed Computing in Sensor Systems and Workshops (DCOSS)*, 2011 International Conference on. (2011), 1-3
4. Maurtua, I., Kirisci, P. T., Stiefmeier, T., Sbodio, M. and Witt, H. A Wearable Computing Prototype for supporting training activities in Automotive Production. In *Applied Wearable Computing (IFAWC)*, 2007 4th International Forum on. (2007), 1-12.
5. Roggen, D., Magnenat, S., Waibel, M. and Troster, G. Wearable Computing. In *Robotics & Automation Magazine*, IEEE 18, 2. (2011), 83-95.
6. Sagha, H., del R Millan, J. and Chavarriaga, R. Detecting and Rectifying Anomalies in Body Sensor Networks. In *Body Sensor Networks (BSN), 2011 International Conference on.* (2011), 162-167.
7. van Laerhoven, K., Schmidt, A. and Gellersen, H. W. Multi-sensor context aware clothing. In *Wearable Computers (ISWC)*, Sixth International Symposium on. (2002), 49-56.