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A practical multi-sensor activity recognition system for home-based care

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ABSTRACT

To cope with the increasing number of aging population, a type of care which can help prevent or postpone entry into institutional care is preferable. Activity recognition can be used for home-based care in order to help elderly people to remain at home as long as possible. This paper proposes a practical multi-sensor activity recognition system for home-based care utilizing on-body sensors. Seven types of sensors are investigated on their contributions toward activity classification. We collected a real data set through the experiments participated by a group of elderly people. Seven classification models are developed to explore contribution of each sensor. We conduct a comparison study of four feature selection techniques using the developed models and the collected data. The experimental results show our proposed system is superior to previous works achieving 97% accuracy. The study also demonstrates how the developed activity recognition model can be applied to promote a home-based care and enhance decision support system in health care.

1. Introduction

The number of aging population worldwide has increased rapidly. In 2010, there were 520 million people aged 65 years and over and is expected to increase to 1.9 billion people in 2050 [1]. Population aging affects people in various aspects from society, politics to health care. Health care in particularly is greatly affected as people's health deteriorate as they get older. These effects include high demand in long-term care, poor standard of care, and financial constraints in care expenditure. Different studies have been carried out with the aim of overcoming these effects. For example, an autonomous intelligent system was proposed in [2] for planning nurses' working time in order to provide effective care to Alzheimer patients. The influencing factors that lead to initiate adoption of healthcare information systems were studied in [3]. The investigation was conducted in [4] to identify the level of autonomy–disability of elderly people living in a nursing home for forecasting, planning and management of healthcare and social services.

Due to the effects of an increasing older population, it is important to encourage preventive care to help prevent acute illness or delay entry into institutional care e.g. nursing homes, hospitals, etc. Examples of preventive care are aging healthy and home-based care. Healthy aging are such as eating healthy, regular exercising, regular health check-up, etc. Aging healthily could extend longevity and reduce the possibility of acute serious illness. Another preventive care is to provide care at home such as health monitoring, activity monitoring, etc. Home-based care allows elderly people to be monitored seamlessly from their own homes allowing them to remain at home as long as possible. With current advance in sensors and technology, home-based care is possible and affordable for general population.

Activity recognition is a part of home-based care. By manipulating and mining sensor data, the current activity of a person can be determined. This information can be used to provide home monitoring, detect early sign of deterioration, provide a means of assurance for family members, etc. Prior works in activity recognition are usually performed through visual sensing. However, this is not practical for elderly care application due to privacy issues resulting from the use of cameras. Due to this reason, a non-visual based activity recognition approach is more suitable. Recently, non-visual based activity recognition [5,6] has been studied in an attempt of proposing a model that is practical and highly accurate.

Although these studies have demonstrated that activity recognition can benefit from combining information from multiple sensors, it is not yet clear how each of the sensors helps in the detection of human activities. In this paper, we investigate seven types of sensors including accelerometer, temperature, altimeter, heart rate monitor, gyroscope, barometer and light sensor to understand how the loss of a particular sensor affects the classification accuracy and to which type of activity. We have collected a real data set from a group of elderly people performing a range of daily activities. This paper also studies several feature selection techniques and classification techniques in order to propose a practical activity recognition model. We compared our approach with other studies to demonstrate the superior in our model.

2. Related works

Based on sensor location, there are two main approaches in activity recognition i.e. infer activity from detected objects or changes in

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environment and infer activity from movement data. Object-based activity recognition requires sensors to be attached to numerous objects such as cups, toothbrush, tooth paste, spoon, etc. within homes. Sometimes sensors are also placed in environment for example, door switch [7], RFID [8], and motion detectors [7] in rooms. This approach infers activity by observing the sequence of objects used or changes in environment. Although the approach can provide clear semantic toward activity recognition, it requires a large number of sensors installed in homes. Also, when there is a new object, a sensor must be tagged and the system needs to be updated. Problems related to uncertainty e.g. false start and fail to detect object can affect recognition performance. To address the problems, the approach which infers activity from movement data obtained from on-body sensors is adopted.

Human activity recognition based on on-body sensors has become popular due to the advance in sensor technology making sensors more accessible and affordable. A variety of on-body sensors have been explored such as accelerometer [5,7–11], gyroscope [6, 11], temperature [6,7,9], etc. Accelerometer is shown to be the most powerful sensor for activity recognition as it responds fast to movement change and can reflect the type of activity well [9]. A number of studies use several sensors attached to different parts of human body to increase recognition accuracy. Locations such as chest [10,11], wrist [5–7,11], thigh [10], waist [12], ankle [10,11], etc. have been studied. For example, accelerometers were used on subjects' wrists, ankles and chest [11]. Inertial sensors were attached to chest, right thigh and left ankle to detect postures and transition activities [10]. However, attaching several sensors on body may decrease mobility or even obstruct daily activity routine. Also, these sensors may sometimes be perceived as stigmatization. It is important, especially for elderly care applications, that the activity recognition system is practical with high performance.

Taking aforementioned issues into consideration, some of studies proposed an activity recognition model based on a single location on human body [5]. Wrist is an ideal location for on-body sensors as it will not obstruct daily activity mobility. In this paper we consider the use of multiple sensor worn on wrist as we hypothesize that they will help yield more information necessary for activity recognition. Some studies were carried out based on wrist-worn multi-sensors. Multi-sensor wrist-worn equipment was used to detect walking, walking upstairs, walking downstairs, sitting and running activities [5]. The study showed that using a combination of accelerometer and light worn on wrist can produce good classification accuracy. Accelerometer, temperature sensor and altimeter worn on wrist were used to detect nine activities [6]. It showed that by combining accelerometer with temperature sensor and altimeter, classification accuracy is improved. Although the literatures indicated good results on the use of multiple sensors, it is not yet clear how each of the sensor helps in activity classification. This prompted us to investigate how the loss of a particular sensor will affect the classification accuracy. Seven sensors have been selected including accelerometer, temperature, altimeter, gyroscope, barometer, light, and heart rate monitor. These sensors have been used in several prior works [5–9,12–15]. A study showed that by using gyroscope and magnetometer with accelerometer, the classification accuracy is increased by 17% [13]. Accelerometer and barometer were used to detect 11 children activities [12]. The results indicated improvement in accuracy after adding barometer. Accelerometer and light sensor were used in [14] to detect seven office worker activities. A study showed that combining acceleration and heart rate improves the accuracy of estimation of energy expenditure by 1.4% [15].

Based on these sensors, we propose an activity recognition model where we investigated several feature selection and classification techniques. As feature space becomes larger when several sensors are used, it is important that only important and relevant features for classification are selected. The feature selection technique usually measures the relationship between feature and the output such as by using information theory [16–18], or by measuring the variable salient using neural network [6,19], etc. For example, Minimal Redundancy Maximal Relevance (mRMR) [16] employs information theory to find a subset of features that have high mutual information between feature and output (maximal relevance) and low information among the selected features (minimal redundancy). Normalized Mutual Information Feature Selection (NMIFS) [17] is another technique which uses information theory. It claimed to be an enhancement over mRMR where normalized MI is used as a measurement of redundancy to reduce the bias of MI toward multi-valued features and also constraint value to be in [0 1] range. Feature Combination (FC) technique uses neural network theory to perform feature selection. FC [6] takes into account a combination of feature to monitor network performance while features are added to the network. In this paper, we combine Clamping [19] with mRMR and NMIFS and compare it with other feature selection techniques including mRMR, NMIFS, and FC. Several classification algorithms such as Support Vector Machine (SVM) [6,7,12], neural network [6,9,11], Decision Tree [8,9,12,5], etc. have been studied in human activity recognition. In this study, SVM, MLP, and RBF are investigated.

3. Methodology

3.1. Multi-sensor activity recognition system

This section presents a practical multi-sensor activity recognition system shown in Fig. 1 and describes how it can be used for home-based care. The elderly person wears sensors including accelerometer, temperature sensor, altimeter, gyroscope, light sensor, and barometer which are embedded on watch on their wrists and a heart rate monitor on their chests. The data from the sensor is continuously transmitted wirelessly through radio frequency to the PC in the elderly's home. The PC contains the activity recognition model (AR) which can recognize and detect daily activities of a user. The detected activity is perceived wirelessly by a companion robot who provides assistances or services based on the current activity. For example, if the robot detects that the elderly person is exercising, it can play music or video related to that exercise. If the house is equipped with smart sensors, the detected activities can be used to provide information for adaptive services. For example, if it is detected that a user is sleeping, the light and the temperature can be adjusted to the suitable condition.

The detected activities can also be used by carer, health professionals, and families. To protect the privacy of the elderly person, the system will not send the raw sensor data over the network. The detected activities are encrypted when sent over the Internet. For carers, their systems will contain an activity abnormal detection model to detect abnormality of the elderly person. When the abnormal activity is detected, a carer can visit the elderly home and provide help. This will allow independence for both elderly person and carer, while maintaining safety and good care when necessary. The families of the elderly person will also benefit from the system where they can use it to monitor them online anywhere and anytime to provide a peace of mind that their love ones are doing well. Health professionals will have access to the activity records. Their systems will contain a model which interprets each activity into activity patterns. They can use this as a complement to normal independent assessment and to support illness diagnostic. Also, if they detect any changes in behavior, they could send a request to elderly person's system to retrieve a raw sensor data for further analysis or arrange a home or hospital visit for a check up on the elderly person.

Any sensor data sent from the elderly person must be encrypted and authorization system must be installed and used whenever someone requested to access the data. Also, there must be a signed agreement on who can have access to what information and the elderly must give their consent prior to the use of the system to ensure privacy and visibility.