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Activity Recognition Using Dynamic Multiple Sensor Fusion in Body Sensor Networks*

Lei Gao, Alan K. Bourke and John Nelson

***Abstract*— Multiple sensor fusion is a main research direction for activity recognition. However, there are two challenges in those systems: the energy consumption due to the wireless transmission and the classifier design because of the dynamic feature vector. This paper proposes a multi-sensor fusion framework, which consists of the sensor selection module and the hierarchical classifier. The sensor selection module adopts the convex optimization to select the sensor subset in real time. The hierarchical classifier combines the Decision Tree classifier with the Naïve Bayes classifier. The dataset collected from 8 subjects, who performed 8 scenario activities, was used to evaluate the proposed system. The results show that the proposed system can obviously reduce the energy consumption while guaranteeing the recognition accuracy.**

I. INTRODUCTION

The importance of monitoring activities of daily living (ADL) to promote a healthier lifestyle is now widely accepted. Maintaining regular activities is particularly important for the improved well being of an aging population. Therefore, there has been a substantial amount of research studies using wearable sensor network for monitoring activity of daily living. The examples of these are monitoring patients with chronic diseases and detecting emergency situations for independent living older adults. Currently, inertial sensors such as accelerometers and gyroscopes are appropriated and widely used for activity recognition.

There has been significant studies carried out on activity recognition using multiple sensors attached to different body positions due to its high recognition accuracy and low computational load for each sensor [1][2]. However, the challenge of adopting multi-sensor system is the high energy consumption of the battery when the wireless communication is left on continuously. Dynamic multiple sensor fusion based on the sensor selection algorithm has been investigated to cope with this challenge [2]. Concurrently, a two-stage Bayesian classifier is adopted to solve the features vector change problem [1]. However, the Naïve Bayes classifier, with the limitation of strong independence assumption, is not an efficient classifier for multi-sensor classification. There are two challenges introduced by the dynamic multiple sensor fusion algorithm as follows.

- Sensor selection algorithms have been heavily investigated in the field of signal processing. However, there is little work applying these algorithms to body sensor networks.
- There has been a number of attempts to apply modern classifiers to single-sensor systems for activity recognition. A hierarchical classifier which is efficient and suitable for dynamic sensors fusion systems needs to be investigated and proposed.

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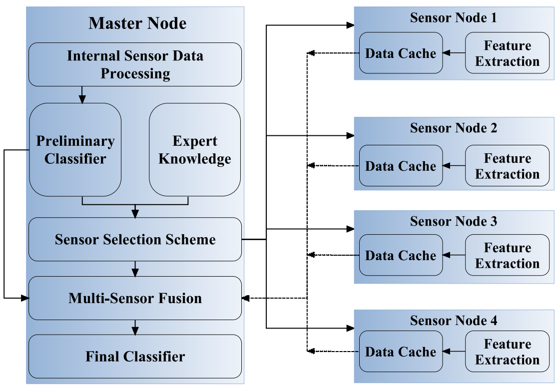

Fig. 1. The framework using dynamic multiple sensor fusion for activity recognition.

In this study, a novel wearable system based on dynamic multiple sensor fusion is proposed for activity recognition. In the proposed system, a real-time sensor selection algorithm and a hierarchical classifier based on the decision tree are the main contributions. The dataset collected in the eCAALYX project [3] is used to evaluate the system.

II. METHODOLOGY

A. System Architecture

In this study a framework, which consists of a master node and four sensors, is proposed for activity recognition as shown in Fig. 1. In the sensor sides, the signal preprocessing and the feature extraction can be completed in each sensor, and then the feature vector extracted can be stored in the data cache module of each sensor.For each sensor, two algorithms are adopted for signal preprocessing to fix the problems of the sensor calibration and alignment, which are two factors affecting the performance of wearable systems. The proposed algorithm transforms the acceleration signal from the device coordinate system to the body reference coordinate system relative to gravity. Further detail on these algorithms can be found in our previous work [4].

A smart phone is usually adopted as the master node. In the master node, there is also an accelerometer , which works simultaneously with other sensors. The feature vector from the inertial sensor of the master node is fed into the preliminary classifier. The sensor selection scheme in the master node, which combines the result from its preliminary classifier and the expert knowledge, chooses the sensor subset and sends the data query to these sensors. The multi-sensor fusion module collects the chosen sensor data, and each sensor flushes the data cache. Finally, the classifier in the master node distinguishes the activity using the feature vector collected. The Naïve Bayes classifier is used for the preliminary classification due to its easy implementation and its suitability to attain a priori probability. The expert knowledge is defined as the distinguishing ability of a sensor subset to recognize different activities, which is obtained using in the training stage. The combination of a priori probability and the expert knowledge can predict the best sensor subset for real-time activity recognition. The Decision Tree classifier is used as the final classification algorithm due to its excellent performance for activity recognition. In addition, the feature vector for the final classifier fuses the information both from the preliminary classifier and the selected sensor subset.

B. Sensor Selection

The sensor selection problem can be defined as follows: Given a set of sensors $S = \{S_1, \cdots, S_k\}$, determine the subset $S^{'}$ of k sensors to satisfy the requirements of one or multiple missions. The subset is one which achieves a tradeoff of energy constraints and quality of information with respect to its task. However, it is a major challenge to determine the contribution of each sensor without retrieving its data. A number of research studies focus on the algorithms for predicting the contribution of each sensor based on some special information, such as [5].

In this study, the sensor selection problem is to minimize the transmission energy of the network while guaranteeing the recognition accuracy. It is hard to determine the recognition accuracy without obtaining the data. This study adopts the probability of misclassification to predict the recognition accuracy.

Lainiotis et al. [6] provides an upper bound on the probability of misclassification, which is used to define the performance requirement that must be met while minimizing the transmission power, given as

$$P(\epsilon) \leqslant \sum\nolimits_{i<j} (P_i(X)P_j(X))_{1/2}\rho_{ij} = P_{ub}(\epsilon) \qquad (1)$$

Where $P_i(X)$ and $P_j(X)$ are a priori probabilities of hypotheses H_i and H_j from the current state, respectively, and ρ_{ij} is the Bhattacharyya coefficient, which is a measure of the confusability of the two hypotheses, and is defined as [7]

$$\rho_{ij} = \int \sqrt{p_i(x)p_j(x)dx} \qquad (2)$$

Where $p_i(x)$ and $p_j(x)$ are the multivariate densities associated with hypotheses H_i and H_j, respectively. In the case of the multivariate Gaussian, if $p_i(x) = N(m_i, \sum_i)$, the upper bound in (1) can be rewritten as

$$P_{ub}(\epsilon) = \sum\nolimits_{i<j} \exp[-\sum_{k=1}^{K} \varphi_{ij}(k) + \frac{1}{2}\log(P_i(X)P_j(X))] \qquad (3)$$

where

$$\varphi_{ij}(k) = \frac{1}{8}(m_{ik} - m_{jk})^T \sum\nolimits_{hk}^{-1} (m_{ik} - m_{jk}) + \frac{1}{2} log \frac{\det \sum_{hk}}{\sqrt{\det \sum_{ik} \cdot \det \sum_{jk}}} \qquad (4)$$

$\varphi_{ij}(k)$ can be obtained from the training dataset, and $P_i(X)$ and $P_j(X)$ are gotten from the priori probabilities obtained using the preliminary classifier.

Therefore, the sensor selection problem for activity recognition in body sensor networks is defined as

$$\begin{array}{ll} \text{minimize} & \text{sum(z)} \\ \text{subject to} & \begin{cases} f(P_{ub}(\epsilon)) \leq \tau \\ z_k \in \{0,1\}, \qquad k = 1, \cdots, K \end{cases} \end{array} \qquad (5)$$

Where z_k is the optimization vector which represents whether the sensor is employed, $f(P_{ub}(\epsilon))$ is the upper bound of the probability of misclassification using the selected sensor subset and τ is the threshold of $f(P_{ub}(\epsilon))$. The sensor selection problem, then, can be formulated as a convex optimization problem. Therefore, the problem can be solved using the convex optimization [8].

C. Hierarchical Classifier

Most of these studies, investigating hierarchical classifiers, adopt a multi-stage classifier design method, which design each level classifier independently. Therefore, the information obtained from the previous classifier cannot be used adequately in the next classifier. Concurrently, the dynamic sensor fusion system introduced another problem: missing feature values. As the sensor subset is changed according to the real-time information, the feature vector fed into the final classifier is not fixed. In order to improve the hierarchical classifier efficiency and cope with the missing feature value problem, a hierarchical classifier, which is based on the Decision Tree design from the statistical theory point of view, is proposed. The proposed hierarchical classifier consists of two layers: the preliminary classifier and the final classifier as shown in Fig. 1.

In this study, the Naïve Bayes classifier is adopted as the preliminary classifier. This classifier is a classical one with strong feature independent assumption. It can not only predict the current activity, but also obtain the class distribution. In the proposed framework, the class distribution is used as the priori probabilities for the sensor selection module. In parallel, it is also fed into the final classifier to improve the performance and cope with the missing feature value problem. In the proposed system, the features for the preliminary classifier are obtained using the internal sensor of the master node, which records simultaneously with other sensors.

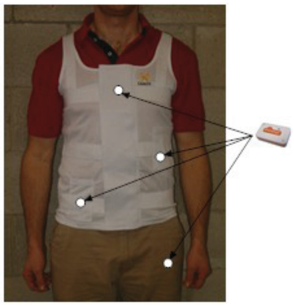

Fig. 2. The smart garment for activity recognition in the eCAALYX project.

In this study, the Decision Tree classifier is used as the final classifier. The C4.5 algorithm for the Decision Tree classifier proposes a solution for coping with the missing feature values [9]. We combine the Naïve Bayes classifier and the Decision Tree classifier as a statistical process. The class distribution obtained from the Naïve Bayes classifier is used as the feature attributes to feed the Decision Tree classifier.

III. RESULTS

In this study, the dataset for evaluation was collected in a study conducted by the eCAALYX project, in which eight subjects were recruited for the trial. The recognition accuracy and the energy consumption of the proposed system were investigated using the collected dataset.

A. Data Collection

In the eCAALYX project studies, a smart garment with four sensors integrated into a WBAN (Wireless Body Area Network) is used to determine the optimum location for a single or multi-sensor solution for monitoring the activity of daily living as shown in Fig. 2. In the smart garment, the Shimmer wireless sensor platform was adopted to collect the mobility information [10]. Concurrently, a laptop was used to control the sensors and collect data through a Bluetooth module.

In this study, the eight subjects were recruited for the trial, which ranged in age from 70 to 83 $(76.50 \pm 4.41 years)$. The dataset for activity recognition is not directly obtained from the supervised activity performed by each subject, but extracted from the different scenarios of daily living. Each subject was asked to perform eight scenario activities as shown in Table 1 with four sensors simultaneously recording, and each scenario activity is repeated three times. The signal is then divided into several components which are the activities for research as shown in Table 2. For example, Case 1 can be divided into standing, transition, sitting, transition, and standing as shown in Fig. 3. The reason why the scenario activity is adopted is that we can evaluate the wearable system using the datasets collected in a real-life environment. In particular for Case 4, subjects were asked to walk upstairs and downstairs freely. There was no specified routine for this activity. It is a challenge to distinguish it from walking.

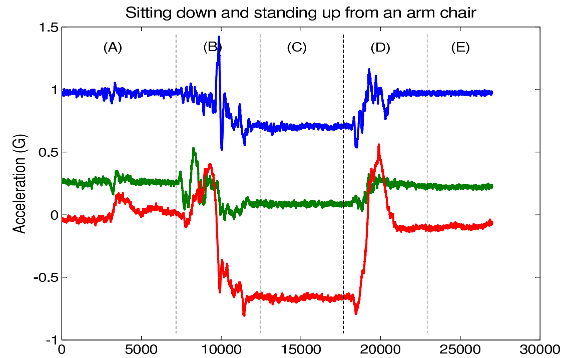

Fig. 3. The annotation of the scenario activity: (A) Standing, (B) Transition, (C) Sitting, (D) Transition and (E) Standing.

TABLE I
SCENARIO ACTIVITY

Num	Description
Case 1	Sitting down and standing up from an arm chair
Case 2	Sitting down and standing up from a kitchen chair
Case 3	Sitting down and standing up from a toilet seat
Case 4	Walking up and down stairs
Case 5	Sitting down and standing up from a bed
Case 6	Lying down and getting up from a bed
Case 7	Getting in and out of a car seat
Case 8	Walking 10m

TABLE II
ACTIVITIES OF DAIL LIVING

State	Activity
Static	Lying Sitting Standing
Dynamic	Walking Walking up and down stairs
Transition	Lying-Standing Standing-Lying Sitting-Standing Standing-Sitting Walking-Standing Standing-Walking

B. Results and Discussion

In this study, Matlab was used to process and analyze the collected dataset and the WEKA [11] software was used to evaluate the performance of the proposed classifier. We used the data from the waist sensor to simulate the master node internal accelerometer, which was sent into the preliminary classifier to obtain the class distribution.

The mean feature was adopted for the preliminary classifier and the final classifier, which was a computing affordable and efficient feature. In this study, we didn't select computing high-weight features, because multiple sensor fusion was actually used to distribute the feature extraction process into the sensor network. The sampling rate was 20Hz and the window size was 1s without overlap. The leave-one-out procedure was used to evaluate the performance of the classifier, which meant that seven subjects' datasets were

TABLE III
THE COMPARISON OF THE CLASSIFIERS: OC (ORIGINAL FOUR SENSOR CLASSIFIER), NB (TWO-STAGE NAÏVE BAYES CLASSIFIER) AND HC (PROPOSED HIERARCHICAL CLASSIFIER)

	Stand	Sit	Lie	Walk	Stairs	Trans	Overall
OC	99.2	98.7	99.7	97.3	75.8	88.0	95.5
NB	91.3	78.7	100.0	78.7	31.7	33.8	76.33
HC	96.6	98.9	99.7	96.0	72.3	76.7	92.7

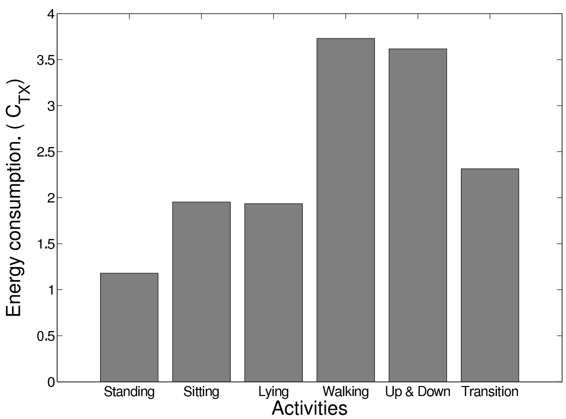

Fig. 4. The energy consumption due to the Bluetooth transmission.

used as the training data and the other one was used as the testing data. This procedure was repeated 8 times with different testing subject. In this section, the recognition accuracy of the proposed system and the energy consumption due to the wireless transmission were investigated with the dataset.

Table III shows the comparison of the recognition accuracies with the different classifiers as follows: the Original Four Sensor classifier (OC), the Two-Stage Naïve Bayes classifier (NB) and the proposed Hierarchical classifier (HC). For OC, there was not the sensor selection module. The dataset with all four sensors was used to train and test the Decision Tree classifier. For NB, the sensor selection module was adopted. The training dataset was from all four sensors, but the testing dataset were the dynamic feature vectors. The two-stage Naïve Bayes classifier was adopted [1]. For HC, the training dataset and the testing dataset were similar to the ones for NB. However, the proposed hierarchical classifier was used to recognize the activities.

Table III demonstrates that HC achieved similar recognition accuracy to OC, with a reduction by 2.8%. However, NB had a large recognition accuracy drop of 19.2%, compared to OC. In particular, HC had much better performance for the dynamic activities including Walking, Up and Down Stairs and Transition.

Fig. 4 shows the energy consumption when recognizing different activities due to the wireless transmission in the proposed systems. We define that the energy consumption, when keeping all four sensors working, is 4 C_{TX} due to the communication using the Bluetooth interface. When using the sensor selection algorithm, the energy consumption for those easy recognizable activities is reduced due to fewer sensors employed. We used the dataset collected from all 8 subjects to obtain the average energy consumption for each activity.

Fig. 4 illustrates that the energy consumption for the static activities was between 1 C_{TX} and 2 C_{TX}, but was between 2 C_{TX} and 3.5 C_{TX} for recognizing the dynamic activities. The average energy consumption when employing the sensor selection module was 2.5 C_{TX}. Compared to the use of all four sensors, the algorithm could reduce the energy consumption approximately by 37.5%.

IV. CONCLUSIONS

In this paper, we proposed a framework, which consisted of the sensor selection module and the hierarchical classifier, to dynamically fuse multi-sensor data. The dataset conducted by the eCAALYX project, which recruiting 8 subjects to perform 8 activities in real-life scenario, was used to investigate the recognition accuracy and the energy consumption of the proposed system. The results demonstrated this system could just reduce the recognition accuracy by 2.8%, but save 37.5% of the consumption energy compared to using four sensors.

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