Robust Human Activity Recognition Using Smartphone Sensors via CT-PCA and Online SVM

Zhenghua Chen, Qingchang Zhu, Yeng Chai Soh, and Le Zhang

***Abstract*—Human activity recognition using either wearable devices or smartphones can benefit various applications including healthcare, fitness, smart home, etc. Instead of using wearable devices which are intrusive and require extra cost, we shall leverage on modern smartphones embedded with a variety of sensors. Due to the flexibility of using smartphones, the recognition accuracy will degrade with orientation, placement, and subject variations. In this paper, we propose a robust human activity recognition system in terms of orientation, placement, and subject variations based on coordinate transformation and principal component analysis (CT-PCA) and online support vector machine (OSVM). The proposed CT-PCA scheme is utilized to eliminate the effect of orientation variations. Experiments show that the proposed scheme significantly improves the activity recognition accuracy and outperforms the state-of-the-art methods on leave one orientation out experiments, which demonstrates the generalization ability of the proposed scheme on the data from unseen orientations. We also show the effectiveness of this scheme on placement and subject variations. However, the inherent difference of signal properties for different placement and subject dramatically reduces the recognition accuracy, especially for different placement. Thus, we present an efficient OSVM algorithm, that is, online-independent support vector machine (OISVM), which utilizes a small portion of data from the unseen placement or subject to online update the parameters of the SVM algorithm. The experimental results demonstrate the effectiveness of this OISVM algorithm on placement and subject variations.**

***Index Terms*—Coordinate transformation, human activity recognition, online support vector machine (OSVM), principal component analysis (PCA), smartphone sensors.**

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I. Introduction

HUMAN activity recognition using wearable or smartphone sensors benefits a myriad of applications, such as healthcare, fitness, smart home, etc. For instance, medical staffs can monitor the health conditions of elders based on their activity information [1]. According to users' activity level, we can estimate their daily energy expenditure and provide exercise advice accordingly [2]. Moreover, smart home research utilizes occupant activity information to maintain a comfortable environment as well as achieve a high energy efficiency [3].

Vision-based activity recognition has been well developed for decades. A view-based daily activity recognition system is developed in [4]. Song *et al.* presented a distributed camera networks for tracking and activity recognition [5]. Tran and Trivedi developed a three-dimensional (3-D) upbody posture recognition system with multiple cameras in [6]. One problem of these vision-based approaches is that the performance of these systems will be greatly affected by the illumination condition of the environment. Moreover, since the cameras are fixed in certain places, the continuous monitoring of a particular user is not possible. Last but not least, these vision-based systems will also suffer privacy concerns in some places, such as bathrooms and bedrooms. Wearable inertial sensors are also popular for human activity recognition [7]. However, the approaches based on wearable inertial sensors require extra sensing components, which are intrusive for users, especially in long-term monitoring. With current development of the smartphone technology, smartphones are not only communication devices, but also powerful sensor platforms. A large amount of sensors are embedded in smartphones, including accelerometer, gyroscope, proximity sensor, humidity sensor, etc. Since smartphones are widely used in our daily life and nonintrusive for users, they can be a good candidate for human activity recognition [8].

Some issues will be encountered on smartphone-based human activity recognition systems. For wearable sensor-based systems, their orientations and placements of devices are fixed in most situations [9], [10]. But this rarely holds for smartphones-based systems because of the flexibility of using smartphones. Due to the varying orientation, placement, and subject, the characteristics of smartphone sensor signals for the same activity shall be quite different, which will significantly degrade the recognition accuracy. For the same subject, due to different clothing for different days, the orientation and placement of the smartphone can be varying. Even in the same placement, the orientation of the smartphone will be changing when performing dynamic activities, such as walking and running. For different subjects, since the clothing, body shape, and behavior of them may have huge difference, the orientations and placements of smartphones will be quite diverse. To address these issues, in this paper, we present a coordinate transformation and principal component analysis (CT-PCA) scheme and an online support vector machine (OSVM)-based online updating algorithm to eliminate the effects of orientation, placement, and subject variations. Since acceleration has been shown to be effective for human activity recognition [11], [12], we only utilize acceleration sensor data in this study. The activities include static, walking, running, going upstairs, and going downstairs, which are the most common activities in our daily life. After our proposed data preprocessing scheme, that is, CT-PCA, time and frequency domain features are extracted from a sliding window of data. Then, various classifiers can be utilized to recognize human activity. During experiments, we first investigate our proposed CT-PCA scheme on orientation-independent, placement-independent, and subject-independent experiments. Then, we shall explore the effectiveness of an efficient OSVM algorithm, that is, online-independent support vector machine (OISVM), on placement and subjection variations which will cause the inherent difference of signals.

The main contributions of this paper are summarized as follows.

1) We propose a CT-PCA scheme to eliminate the effect of orientation variations which is one of the most serious problems in smartphone-based human activity recognition system.
2) We employ real experiments to verify the effectiveness of the proposed scheme and compare it with state-of-the-art methods on leave one orientation out experiments, which can show the generalization ability of the algorithms on the data from unseen orientations. The classifiers with our proposed CT-PCA scheme presents an average improvement of 27.84% over the classifiers with the original data. Meanwhile, our proposed scheme shows the improvements of 12.03% and 18.45% in placement and subject-independent experiments, respectively, which indicates the usefulness of this scheme on placement and subject variations.
3) We present an efficient OSVM algorithm, that is, OISVM, to enhance the performance of the recognition system with the inherent difference of signals caused by placement and subject variations. In real experiments, the OISVM presents an improvement of 10% with 50% of data from the new placement. But it shows smaller improvements on placement-independent experiments.

The rest of the paper is organized as follows: Section II introduces some related works on human activity recognition using smartphone sensors. Section III demonstrates our proposed CT-PCA scheme, followed by feature extraction from the processed data. The generic classification algorithms and an efficient OSVM algorithm are also presented in this section. Section IV introduces experimental setup and data acquisition process. Then, the experimental results and discussions are presented. Section V concludes this work and gives some potential future works.

II. Related Works

Some advanced works have explored human activity recognition using smartphone sensors. Wang *et al.* presented a hybrid feature selection method, which combines the filter and the wrapper methods in considering the tradeoff between time and accuracy [13]. After selecting the best features, two classification algorithms of naive Bayes and *k*-nearest-neighbor (KNN) were applied with four different performance measures. The data for evaluation were collected using a smartphone attached on the waist of the user. This special placement is not suitable for common users, which narrows the applicability of their approach. Tao *et al.* proposed a multicolumn bidirectional long short-term memory (MBLSTM) approach using two directional features for human activity recognition with smartphone accelerometer [14]. The two directional features are extracted from vertical component and the norm of horizontal components of 3-D acceleration. The experiments showed the effectiveness of these two directional features and their proposed deep learning algorithm, that is, MBLSTM, for human activity recognition. However, they did not consider the issues of orientation and placement variations in data collection process, and did not verify the effectiveness of their approach in term of these issues.

Ustev *et al.* [15] proposed an activity recognition system independent of device orientation with linear acceleration. With the help of the gyroscope and the magnetic sensors in smartphones, they transferred acceleration data from the device coordinate system into the fixed earth coordinate system to eliminate orientation variations. The KNN algorithm was utilized for classification. Their experiments demonstrated the effectiveness of their proposed scheme and the KNN algorithm for activity recognition. However, they did not realize that one serious problem arises with the fixed coordinate system, which will be explained in detail in Section III-A. Sun *et al.* [16] proposed an activity recognition approach with varying orientation and position using smartphone acceleration data. They treated the acceleration magnitude as the fourth data dimension together with triaxial acceleration to overcome the effect of orientation variations. During experiments, they indicated the effectiveness of their proposed approach with respect to orientation variations. Moreover, they also tested a generic SVM and a location-specific SVM for each location. The results showed that the location-specific SVM has better performance. However, in real situations, the data from a new location may not be available or adequate for training a specific classifier.

A large number of classification algorithms can be used for human activity recognition. The widely used machine learning algorithms, such as nearest neighbor [17], neural network (NN) [18], naive Bayes [19], decision tree (DT) [1], random forest [20], and SVM [21], can be employed. The algorithms based on fuzzy logic are also powerful for classification tasks [22], [23]. Moreover, the computational intelligence [24], competitive learning [25], and spectral biclustering [26] contain unique

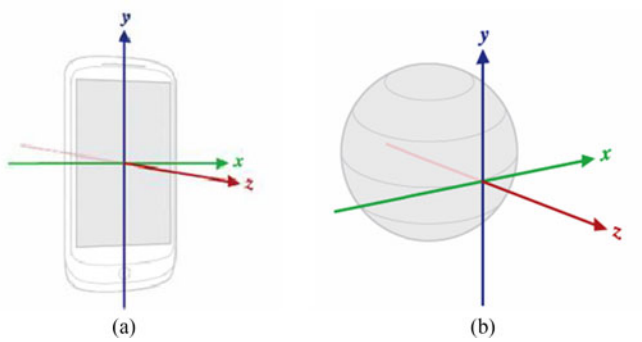

Fig. 1. Coordinate systems [28]. (a) Device coordinate system. (b) Earth coordinate system.

properties for classification. Recently, a new branch of machine learning, that is, deep learning, has been shown to be effective for human activity recognition [14], [27]. However, these deep learning-based approaches require a large dataset for training, which may not be feasible in real life. Since the main contribution of this work is the proposed CT-PCA scheme for orientation variations, we only demonstrate the results on the four classifiers, that is, KNN, DT, NN, and SVM, which have been shown to be effective for human activity recognition in the literature. Note that the other classification algorithms can also be applied with our proposed scheme for human activity recognition.

III. Methodology

A word about our notation and background material. All vectors will be column vectors unless transposed to a row vector by a prime superscript $\top$. Data samples are presented in a M-dimensional space: $\mathbf{x}_i \in \mathcal{X} \subseteq I\!R^M, i \in \{1,\ldots,N\}$. Let $\mathbf{X} \in I\!R^{N\times M}$ be an $N \times M$ matrix obtained by stacking N samples in $\mathcal{X}$, that is, $\mathbf{X} = [\mathbf{x}_1,\ldots,\mathbf{x}_N]^\top$. Let $\mathbf{Y} \in \{y_1, y_2, \ldots, y_N\}^\top$ be a vector obtained by stacking the labels of samples in $\mathcal{X}$, where y_i takes a value from the set of class labels $\{\omega_1, \omega_2, \ldots, \omega_L\}$. We consider L classes classification problem. We will denote a generic data point as $\mathbf{x}$ by ignoring the subscript for convenience, and use $\mathbf{x}_\diamond$ with $\diamond$ denoting the placeholder for the index wherever necessary. We use $\mathbf{x}_{\diamond\bullet}$ to indicate the feature subset indexed by $\bullet$ of the $\diamond$th data.

A. Coordinate Transformation and Principal Component Analysis

Instead of using the original acceleration which contains the gravity component, we apply a 3-D linear acceleration that is widely available in modern smartphones [28]. In wearable-device-based activity recognition systems, the orientations of devices are fixed in most situations. However, this condition will not hold for smartphone-based systems because of the changing clothing, the different body shape, and the changing rotation of the device when performing dynamic activities. Since the outputs of smartphone sensors are along with the device coordinate system which is shown in Fig. 1(a), the data of the three dimensions will change with the changing orientation of the device. This will dramatically degrade the detection accuracy of the activity recognition system. One efficient way to solve that is to transfer the sensor outputs from the device coordinate system into a fixed coordinate system [15]. A potential fixed coordinate system is the earth coordinate system which is shown in Fig. 1(b).

The two most widely used coordinate transformation methods are based on Euler angle and quaternion. The Euler angle-based approach that has been used in [15] may suffer from the problem of *gimbal lock*. We employ a quaternion, which is more efficient and does not have such problem, for the coordinate transformation. It is a four-element vector that can represent any rotation in a 3-D coordinate system. According to [28], a software sensor, named rotation vector sensor, can provide real-time four elements of a quaternion. The quaternion $\mathbf{q}$ can be expressed as

$$\mathbf{q} = \begin{pmatrix} a \\ b \\ c \\ d \end{pmatrix} = \begin{pmatrix} \cos(\theta/2) \\ v_x \sin(\theta/2) \\ v_y \sin(\theta/2) \\ v_z \sin(\theta/2) \end{pmatrix} \tag{1}$$

where v_x, v_y, and v_z are unit rotation of three axes, and θ is the angle of rotation. Based on [29], a rotation matrix $\mathbf{R}$ can be calculated as follows:

$$\mathbf{R} = \begin{pmatrix} 1-2c^2-2d^2 & 2bc-2ad & 2bd+2ac \\ 2bc+2ad & 1-2b^2-2d^2 & 2cd-2ad \\ 2bd-2ac & 2cd+2ad & 1-2b^2-2c^2 \end{pmatrix}. \tag{2}$$

Then, the output in the earth coordinate system can be calculated as

$$\mathbf{V}_e = \mathbf{R}\mathbf{V}_d \tag{3}$$

where $\mathbf{V}_e$ is the outputs in the earth coordinate system, and $\mathbf{V}_d$ is the raw acceleration data in the device coordinate system.

Fig. 2 shows a comparison of acceleration patterns before and after coordinate transformation when a subject performs the activity of walking and the device is put in the backpack with three different orientations (shown in Fig. 3). Since the orientation of the device changes for the three orientations, the acceleration patterns are totally different for the raw data. However, after performing coordinate transformation, the patterns of triaxial acceleration are consistent for the three different orientations. Note that the subject walks to the same geographical direction in this example, therefore, the acceleration data in x-axis and y-axis for the three different orientations after coordinate transformation are the same. The reason why we emphasize this will be discussed in the following paragraph.

Other researchers have utilized different approaches to achieve coordinate transformation [15], [30], [31]. But, to the best of our knowledge, no one realized that one serious problem will arise after this coordinate transformation. As the earth coordinate system is fixed, precisely, x-axis which is tangential to the ground points to the East, y-axis which is tangential to the ground points to the North, and z-axis which is perpendicular to the ground points to the sky [28], one subject that performs certain activity in different directions will yield different acceleration patterns on the x- and y-axes after coordinate transformation, which is unexpected. The left portion of Fig. 4 presents an example. The performed activity is walking and the

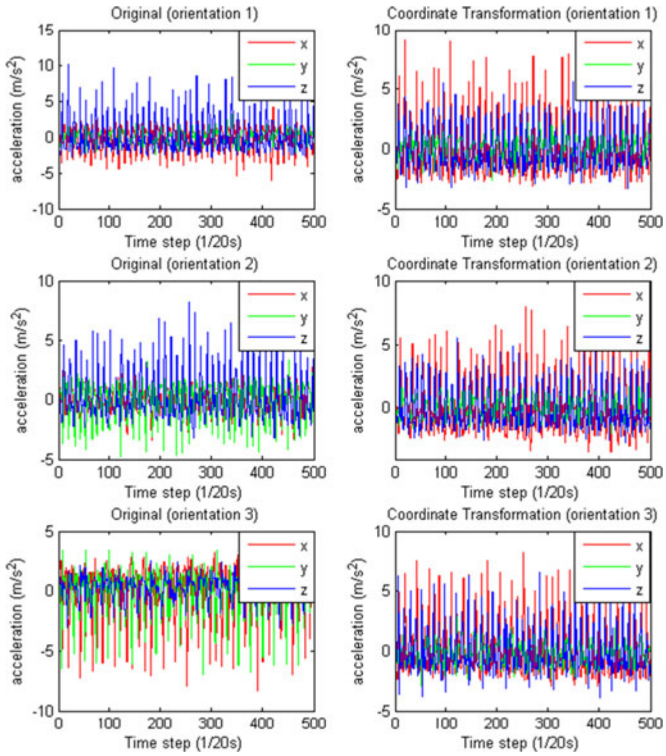

Fig. 2. Before and after coordinate transformation. The performed activity is walking and the placement is the backpack with three different orientations (shown in Fig. 3).

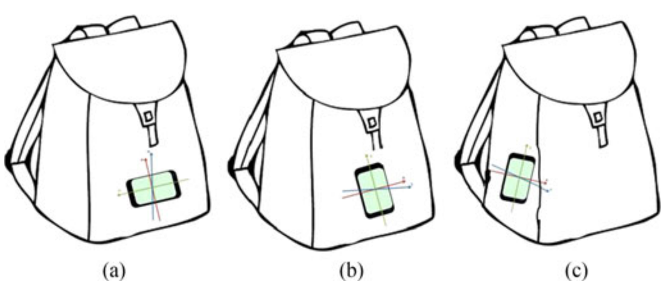

Fig. 3. Three different orientations in the backpack. (a) Orientation 1 (O1). (b) Orientation 2 (O2). (c) Orientation 3 (O3).

walking directions are East, Northeast, and North. We can find that the patterns of acceleration on the x and y-axes are totally different because of different walking directions. To eliminate this direction effect, we can project the acceleration from the fixed x- and y-axes of the earth coordinate system into two orthogonal bases corresponding to the direction of the performed activity and its orthogonal direction. Theoretically, the direction of the performed activity shall have the largest variance of acceleration which can be obtained by using a PCA technique [32]. Then, the direction of the performed activity is exactly the first principal component in PCA, and its orthogonal direction corresponds to the second principal component in PCA. The detailed operation is introduced as follows.

Assume that $\mathbf{a}_x = \left(a_x^1\ a_x^2\ \cdots\ a_x^W\right)^\top$ and $\mathbf{a}_y = \left(a_y^1\ a_y^2\ \cdots\ a_y^W\right)^\top$ denote the accelerations on x-axis and y-axis of a sliding window in the earth coordinate system, and W is the window size. Combining the acceleration data from

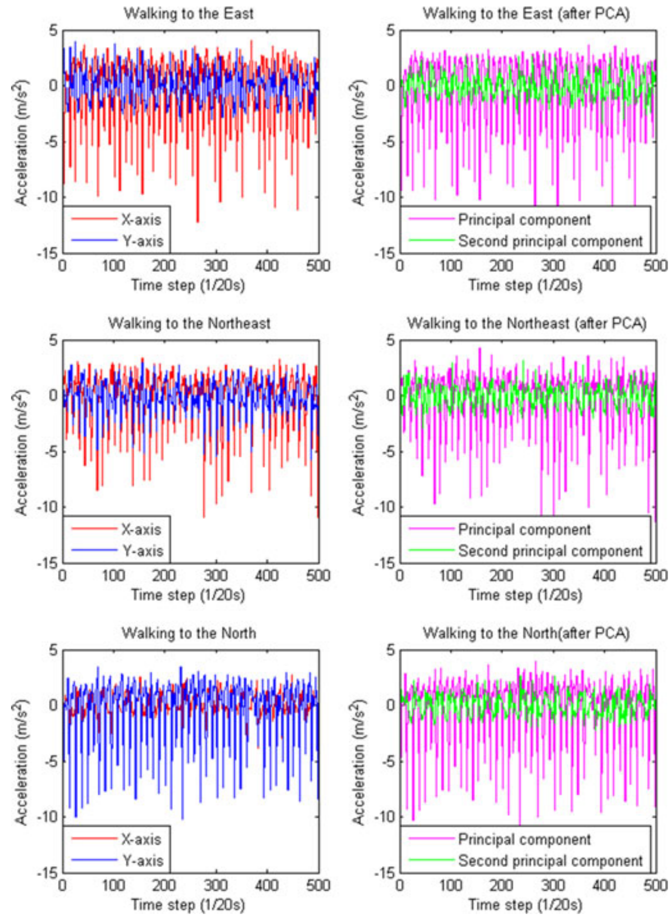

Fig. 4. Before and after PCA. The performed activity is walking and the placement is the backpack with three different directions which are East, Northeast, and North.

the x- and y-axes, we obtain a matrix, $\mathbf{A} \in I\!R^{W\times 2}$, as follows:

$$\mathbf{A} = \begin{pmatrix} a_x^1 & a_y^1 \\ a_x^2 & a_y^2 \\ \vdots & \vdots \\ a_x^W & a_y^W \end{pmatrix}. \tag{4}$$

Then, we can calculate the corresponding covariance matrix $\mathbf{\Omega}$ as

$$\mathbf{\Omega} = \frac{1}{W}(\mathbf{A} - \mathbf{E}(\mathbf{A}))(\mathbf{A} - \mathbf{E}(\mathbf{A}))^\top \tag{5}$$

where $\mathbf{E}(\cdot)$ is the expectation operation for each column of a matrix. Since $\mathbf{\Omega}$ is a symmetric matrix, it can be diagonalized as

$$\mathbf{\Omega} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}^\top \tag{6}$$

where $\mathbf{Q}$ and $\mathbf{\Lambda}$ are eigenvector and eigenvalue matrices of $\mathbf{\Omega}$, respectively. We rank the eigenvalues in descending order and reconstruct the egienvector matrix corresponding to their eigenvalues to obtain a new matrix $\tilde{\mathbf{Q}}$. The PCA transformation matrix can be expressed as

$$\mathbf{P} = \tilde{\mathbf{Q}}^\top. \tag{7}$$

TABLE I
SELECTED FEATURES

Domain	Features
Time	Absolute mean Variance Median absolute deviation Maximum Minimum Signal magnitude range Power Interquantile range
Frequency	Maximum Mean Skewness Kurtosis Power

The final PCA transformation result can be calculated as

$$\mathbf{G} = \mathbf{P}\mathbf{A}^{\top} \tag{8}$$

where the first and second rows of matrix $\mathbf{G}$ are the first and second principal components.

Once the PCA operation is completed, the direction effect can be thoroughly eliminated by using the first and second principal components instead of the accelerations of the x and y-axes in the earth coordinate system. Fig. 4 shows an example of the acceleration patterns before and after the PCA analysis. It can be found that, the acceleration patterns become consistent for the same activity after the PCA operation.

In summary, the ultimate purpose of the proposed CT-PCA is to obtain a consistent acceleration pattern for the same activity without the influence of device orientation variations, which can guarantee a satisfactory performance of the recognition system. Coordinate transformation to the earth coordinate system is a popular way to achieve consistent acceleration patterns in the literature. However, the patterns of acceleration on the x and y-axes in earth coordinate system will be different for the same activity with different directions of the performed activity (see Fig. 4, left part), which is unexpected. To solve this problem, we map the acceleration on the x- and y-axes into the main direction of the performed activity (the direction with the largest variance) and its orthogonal direction by using the first and second principle components of PCA. After performing our proposed CT-PCA technique, the acceleration pattern for the same activity will be consistent with varying device orientations.

B. Feature Extraction

The 3-D acceleration time-series data after CT-PCA is divided into windows. Then, time and frequency domain features are extracted from these windows. Table I lists the features that we used. Many research works have shown the effectiveness of these features [2], [13], [15].

C. Classification

We consider classification as identifying the discrete category of a new observation by learning on training data to obtain

$$y_i = \mathbf{g}(\mathbf{x}_i, \Theta), y_i \in \mathbf{Y}, i = 1, 2, ..., N \tag{9}$$

where $\mathbf{x}_i$ is the ith observation as a feature vector, y_i is the category that this observation belongs to, $\mathbf{g}$ is the trained classification function, and Θ is the classification function's parameter set.

Generic classifiers are applied to validate the effectiveness of our proposed CT-PCA method. Then, we also investigate an efficient OSVM algorithm in handling the poor performance of placement-independent and subject-independent experiments caused by inherent difference of the data.

1) Generic Classifier: Classifiers in [33] and [14] based on deep NN have been shown to have superior performance. But these approaches require a large dataset for training, which may not be feasible in real life. Some generic classifiers, that is, KNN [13], DT [1], NN [34], and SVM [16], have been shown to be effective for human activity recognition with a reasonable size of the data.

2) Online Support Vector Machine: We elaborate the commonly used SVM and its online extension as they play a central role in our human activity recognition system. For the simplicity of presentation, we formulate the problem as a binary classification task, that is, $y_i \in \{+1, -1\}$. Multiclass problem can be easily addressed by well-established methods such as *one-vs-one*.

SVM basically learns a discriminant function with maximum margin in the feature space induced by the mapping function $\phi : R^M \rightarrow R^S$. The discriminant function is defined as

$$f(\mathbf{x}) = \mathbf{w}\phi(\mathbf{x}) + b. \tag{10}$$

The above function can be obtained by solving the following quadratic optimization problem:

$$\begin{aligned} &\min \frac{1}{2}(\|\mathbf{w}\|_2)^2 + C\sum_{i=1}^{N}\xi_i \\ &\text{with respect to } \mathbf{w} \in R^S, \xi \in R_+, b \in R \\ &\text{subject to } y_i(\langle \mathbf{w}\phi(\mathbf{x_i})\rangle + b) \geq 1 - \xi_i, \forall i \end{aligned} \tag{11}$$

where $\mathbf{w}$ and b are the parameters of the discriminant function, C is a predefined positive tradeoff parameter between model simplicity and generalization ability, and ξ_i is a slack variable.

The Lagrangian dual function of the previous problem is as follows:

$$\max \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j \underbrace{\langle\phi(\mathbf{x_i}), \phi(\mathbf{x_j})\rangle}_{K(\mathbf{x_i}, \mathbf{x_j})} \tag{12}$$

where $K : \mathbf{R^D} \times \mathbf{R^D} \rightarrow R$ is the kernel function and α is the dual variable. One can simply employ the commonly used kernel functions, such as Gaussian kernel, RBF kernel, linear kernel (no feature mapping is employed), without explicitly knowing the form of the feature transformation function $\phi(\mathbf{x})$.

Solving this, we can get $\mathbf{w} = \sum_{i=1}^{N}\alpha_i\phi(\mathbf{x_i})$. Hence, the discriminant function can be written as

$$\mathbf{g}(\mathbf{x}_i) = \sum_{j=1}^{N}\alpha_j y_j K(\mathbf{x}_j, \mathbf{x}_i) + b. \tag{13}$$

The patterns of the data from different placement and subjects are sometimes different for the same activity. To enhance the performance of the recognition system with an unseen placement or subject, a good strategy is to exploit previous source knowledge when learning the newly available data from the unseen placement or subject, while at the same time optimizing their overall performance. To this end, we resort to the online SVM algorithm.

The standard SVM algorithm aforementioned operates in a batch manner. Online SVM itself remains to be a challenging task and mainly several approaches have been proposed in the literature. In [35] and [36], batch SVM was adapted to examine one sample at a time and produce a new approximate solution. In these methods, an explosion of the number of support vectors may arise sooner or later. In order to tackle this, a budget on the support vectors needs to be specified as a prior and maintained in the online learning process with some heuristic strategies [37], such as removing the support vector which results in the smallest change to the existing vector.

In this paper, we employ the strategy proposed in [38], known as *OISVM*, which was reported to approximately converge to the standard SVM solution each time when new observations are added. The approximation is controlled via a nonsensitive user-defined parameter. The method works by employing a set of linearly independent observations and projecting every new observation onto the set obtained so far. In this way, the method dramatically reduces time and space requirements, which naturally fits into our scenario, at the price of a negligible loss (sometimes even no loss) in accuracy. Compared with similar algorithms aforementioned, the size of the support vectors obtained by this method can always be bounded which implies a bounded testing time. The detailed algorithm of OISVM can be found in [38].

IV. Experimental Results and Discussions

A. Experimental Setup

Smartphone placements can be flexible for different subjects. In this paper, we investigate three most commonly used placements of pants' pocket, shirt's pocket, and backpack. Due to the size constraints for pants' pocket and shirt's pocket, one orientation is chosen for each placement. In the placement of backpack, the orientation can be much more flexible. Thus, we choose three typical orientations shown in Fig. 3 to investigate the orientation effect. To validate our proposed CT-PCA scheme, we apply leave-one-out cross-validation technique. Precisely, we employ leave one orientation out cross validation in one placement, i.e., backpack. In this way, the data for testing are from an unseen orientation, which can validate the generalization performance of the algorithms. Meanwhile, we compare our proposed approach with two state-of-the-art methods in [14], [16]. In [16], Sun *et al.* applied the magnitude to form augmented features to overcome orientation variations. And in [14], Tao *et al.* leveraged on vertical component and the magnitude of horizontal components of transferred acceleration to eliminate orientation variations. Note that Tao *et al.* in [14] and Sun *et al.* in [16] did not perform leave one orientation out experiments. Instead, they mixed the data from all orientations for training and testing, which guarantees the high detection accuracies in their works. But this cannot verify the generalization performance of their approaches, because they did not show the performance of their approaches on the data from unseen orientations.

Moreover, since different placement and subject have varying orientations, we also explore the effectiveness of our proposed CT-PCA scheme on placement and subject variations by using leave one placement and leave one subject out experiments. In addition to the orientation variations for different placement and subject, the signals contain some inherent difference caused by distinct movement pattern for different placement, different clothing, behavior, and body shape. To solve this problem, we investigate an efficient OSVM algorithm, i.e., OISVM, with increasing the batch of data from the new placement or subject in placement-independent or subject-independent experiments, respectively.

B. Data Acquisition

The acceleration data for experiments were collected by an Android application of a Google NEXUS 4 smartphone. Five subjects are involved in experiments with five activities of static, walking, running, going upstairs, and going downstairs. They performed each activity twice for each placement and orientation with a duration of 30 s. Since we collected data for one orientation in pants' pocket, one orientation in shirt's pocket, and three orientations in backpack, the data of 25 min (30 s $\times$ two times $\times$ five orientations $\times$ five subjects) were collected for each activity with a sampling rate of 20 Hz. Thus, the data points for each activity are $25 \times 60 \times 20$. We choose the sliding window of 5 s with 50% overlap, which is widely used. The sampling frequency is 20 Hz, so each segment contains 100 data points for three dimensions. Time and frequency domain features described in Table I are extracted for each segment. The number of extracted feature is 13 (see Table I) for the acceleration data from each axis. Thus, the total number of features is 39 in this work.

C. Orientation-Independent Experiments

The parameters need to be specified for some generic classifiers, that is, KNN, NN, and SVM. For KNN, the parameter of k, which represents the number of nearest neighbors, is chosen to be 3. For NN, the activation function is chosen to be radial basis function (RBF), and the number of hidden neurons is 26, which is determined by using grid search with cross validation of the training data. For SVM, a linear kernel has been shown to be effective with cross validation of the training data, and the parameter of the regularization term C is determined using grid search with cross validation of the training data. We shall investigate the effectiveness of these approaches for our system. Note that for the classifier of NN which contains randomly assigned initial values of parameters, the results for different runs are distinct. Thus, the classifier of NN is run 100 times, and average results are presented.

In the orientation-independent experiments, we applied the data collected from three different orientations in the backpack (see Fig. 3) and employed the cross-validation technique. In details, we used the data from two orientations for training and

TABLE II
ACCURACY COMPARISON FOR ORIENTATION-INDEPENDENT EXPERIMENTS WITH ORIGINAL, AUGMENTED, BIDIRECTIONAL, AND PROPOSED METHODS IN THE PLACEMENT OF BACKPACK (%)

Orientation	Methods	KNN	DT	NN	SVM
O1+O2 → O3	Original	71.48	65.09	67.43	71.33
	Augmented	74.10	71.61	68.69	74.67
	Bidirectional	90.51	89.45	90.61	91.33
	Proposed	90.52	91.04	91.74	93.56
O1+O3 → O2	Original	80.14	68.29	78.50	79.11
	Augmented	81.38	75.71	79.02	84.00
	Bidirectional	90.05	90.43	95.31	94.89
	Proposed	91.61	93.75	96.07	94.89
O2+O3 → O1	Original	62.69	43.40	41.09	58.44
	Augmented	64.59	43.65	41.27	56.22
	Bi-directional	90.98	88.18	95.47	95.56
	Proposed	92.40	93.12	96.09	96.22
Average	Original	71.44	58.92	62.34	69.63
	Augmented	73.36	63.66	62.99	71.63
	Bidirectional	90.67	89.36	93.80	93.93
	Proposed	**91.51**	**92.64**	**94.63**	**94.89**

"O1+O2 → O3" means the use of the data from orientation 1 and 2 for training and the data from orientation 3 for testing.

the data from the remaining one unseen orientation for testing. Previously mentioned four generic classifiers, that is, KNN, DT, NN, SVM, are employed to identify different activities. We also compared our proposed CT-PCA scheme with original, augmented [16], and bidirectional [14] methods.

Table II demonstrates the detection results of the four different methods. Our proposed CT-PCA method outperforms the other methods for the four generic classifiers on average results. The approach based on original signals performs the worst, which did not consider the varying orientation effects. Another approach using the magnitude to form augmented features [16] has limited improvements, because the unique properties on the three axes are merged when using the magnitude. The bidirectional approach separates the signal into vertical component and the magnitude of horizontal components [14], which did not take the properties of the signals on the orthogonal direction of the performed activity. For example, going upstairs or downstairs will have larger variance of signals on orthogonal directions of the performed activity than normal walking, because two feet always lay on different stairs during going upstairs or downstairs, which shall cause additional movements on the two sides. Note that Tao *et al.* in [14] and Sun *et al.* in [16] did not perform leave one orientation out experiments to show the generalization ability of their algorithms. Our proposed method considers all the useful information on the three directions, that is, vertical direction, the direction of the performed activity on horizontal plane and its orthogonal direction. Thus, it has a superior performance over the other methods. Among the four different classification algorithms, the SVM algorithm with our proposed CT-PCA scheme performs the best, and has an average accuracy of 94.89%. This indicates the good generalization performance of our proposed approach on the data from unseen orientations.

It is a common concern about the time complexity of the proposed algorithm. Our proposed scheme contains a coordinate transformation process and a PCA process. The coordinate transformation is performed by a multiplication of the raw data with a 3×3 rotation matrix $\mathbf{R}$ [see (3)], which shall be very fast. The PCA may be a little bit time consuming. We have tested the processing time of the proposed CT-PCA scheme in this orientation-independent experiment. In the experiment, the processing time for all the testing data (450 samples) is 0.1741 s with a CPU of Intel(R) Xeon(R) E3-1226 3.30 GHz, which is a normal PC. This means that the processing time for each data sample is only 3.9×10^{-4}, which can be neglected.

D. Additional Experiments with More Orientations

To further verify the effectiveness of the proposed scheme for orientation variations, we collected some additional data with six different orientations (shown in Fig. 5) from another eight subjects. This time, each subject performs each activity once with a duration of 30 s. Totally, the data of 24 min (30 s $\times$ one time $\times$ six orientations $\times$ eight subjects) were collected for each activity with a sampling rate of 20 Hz. We used the data from five orientations for training and the data from the remaining one unseen orientation for testing. We also compared our proposed CT-PCA scheme with original, augmented [16], and bidirectional [14] methods.

Table III presents the activity recognition accuracies for the four generic classifiers under the six scenarios. We can find that the recognition accuracies of the four classifiers for the method using original data are better than these of the previous experiment. It is because the data from more orientations, that is, five orientations, are involved in training, so that a similar orientation to the testing one has a higher probability to be involved in training. The methods with augmented data show some improvement over the original ones. Similar to the previous experiment, the approaches using the bidirectional data present significant improvements over the augmented and original approaches. And the approaches based on our proposed CT-PCA scheme perform the best. The average accuracy of the four classifiers with the proposed scheme is as high as 97.05%, and the highest accuracy is 98.43% that is achieved by SVM.

E. Placement-Independent Experiments

To evaluate the impact of different placements, we test three common placements, that is, backpack, pants' pocket, and shirt's pocket corresponding to "P1," "P2," and "P3," respectively. Since we only collected the data from one orientation in the placement of pants' pocket and shirt's pocket, we only use the data from one orientation, that is, O1, in the placement of backpack to maintain consistency of data size in each placement. Leave one placement out cross validation is employed, which means the use of the data from one unseen placement for testing and the data from the remaining placements for training. We evaluate the effectiveness of the proposed CT-PCA method on placement variations.

Table IV illustrates the classification results with the original, the augmented, the bidirectional, and the proposed methods

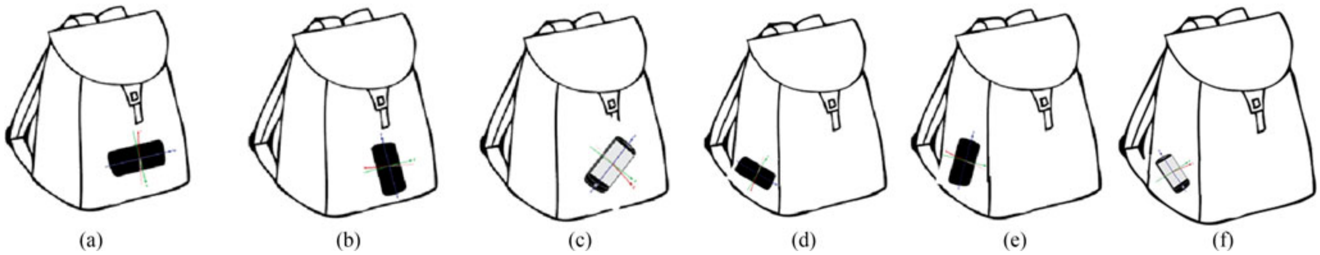

Fig. 5. Additional six orientations in the backpack. (a) Orientation 4 (O4). (b) Orientation 5 (O5). (c) Orientation 6 (O6). (d) Orientation 7 (O7). (e) Orientation 8 (O8). (f) Orientation 9 (O9).

TABLE III
ACCURACY COMPARISON FOR ORIENTATION-INDEPENDENT EXPERIMENTS WITH ORIGINAL, AUGMENTED, BIDIRECTIONAL, AND PROPOSED METHODS IN THE PLACEMENT OF BACKPACK (%)

Orientation	Methods	KNN	DT	NN	SVM
Others → O9	Original	63.86	74.42	78.67	68.33
	Augmented	72.97	82.56	85.22	83.33
	Bidirectional	96.11	96.11	97.94	97.22
	Proposed	98.33	96.09	99.03	99.17
Others → O8	Original	81.03	84.89	88.83	87.50
	Augmented	83.86	82.78	93.33	94.44
	Bidirectional	93.75	95.61	97.14	96.94
	Proposed	94.44	95.28	98.89	99.17
Others → O7	Original	63.36	57.64	71.83	70.28
	Augmented	65.28	69.22	76.25	77.78
	Bidirectional	91.67	92.06	94.08	94.17
	Proposed	93.50	93.42	95.61	96.39
Others → O6	Original	69.92	82.00	73.89	82.50
	Augmented	74.83	82.72	82.25	86.11
	Bidirectional	93.97	96.33	97.42	94.72
	Proposed	98.06	98.60	98.69	98.61
Others → O5	Original	87.31	85.17	87.86	90.83
	Augmented	88.03	83.94	90.81	91.11
	Bidirectional	93.92	93.03	95.67	95.28
	Proposed	93.69	95.33	97.25	98.06
Others → O4	Original	72.64	72.14	60.56	75.83
	Augmented	75.56	68.92	63.47	73.61
	Bidirectional	94.61	92.22	96.50	86.11
	Proposed	97.50	96.42	98.47	99.17
Average	Original	73.02	76.04	76.94	79.21
	Augmented	76.75	78.36	81.89	84.40
	Bidirectional	94.00	94.23	96.46	94.07
	Proposed	**95.92**	**95.86**	**97.99**	**98.43**

"Others → O4" means the use of the data from orientation 4 for testing and the data from the remaining five orientations for training.

TABLE IV
ACCURACY COMPARISON FOR PLACEMENT-INDEPENDENT EXPERIMENTS WITH ORIGINAL, AUGMENTED, BIDIRECTIONAL, AND PROPOSED METHODS UNDER FOUR DIFFERENT CLASSIFIERS

Placement	Methods	KNN	DT	NN	SVM
P1+P2 → P3	Original	70.84	61.12	69.01	71.56
	Augmented	71.30	69.68	72.32	71.33
	Bidirectional	68.44	71.99	78.79	76.00
	Proposed	77.72	73.54	77.20	80.89
P1+P3 → P2	Original	61.53	65.10	59.93	65.78
	Augmented	59.67	59.73	61.44	62.67
	Bidirectional	63.11	63.60	69.04	67.33
	Proposed	66.16	63.82	70.09	74.00
P2+P3 → P1	Original	58.99	60.02	45.21	66.67
	Augmented	60.30	57.39	49.27	69.11
	Bidirectional	72.89	70.79	81.18	74.89
	Proposed	74.61	71.32	86.09	84.67
Average	Original	63.79	62.08	58.05	68.00
	Augmented	63.76	62.27	61.01	67.70
	Bidirectional	68.15	68.79	76.34	72.74
	Proposed	**72.83**	**69.56**	**77.79**	**79.85**

"P1+P2 → P3" means the use of the data from placement 1 and 2 for training and the data from placement 3 for testing.

under four different generic classifiers. It can be found that our proposed method achieves significant improvement over the method with the original data. The reason is that our proposed CT-PCA scheme eliminates the effect of orientation variations for different placement. The augmented method has a similar performance with the method with original data, which further indicates the limited performance of this method on orientation variations. The bidirectional method performs much better than the augmented and the original methods. And our proposed CT-PCA method achieves the best over all the other methods under the four generic classifiers. However, the overall performance on placement-independent experiments is much worse than that on orientation-independent experiments, because the signals of different placement contain inherent difference. For example, the data from pants' pocket will have larger value and variance than that from shirt's pocket during walking due to the movements of legs. We intend to solve this problem of the low detection accuracy caused by the inherent difference of signals by using an online learning method. Among the four different classifiers, the SVM algorithm with our proposed CT-PCA scheme has a superior performance on average results.

F. Subject-Independent Experiments

To evaluate the effect of subject variations, we conduct leave one subject out cross-validation experiments, which means we use the data from any four subjects for training and the data from the remaining one unseen subject for testing. The performance of the proposed CT-PCA method in terms of subject variations is tested.

Table V compares the detection performance on subject-independent experiments with the original and the proposed methods under the four different classifiers. The performance improves around 20% with our proposed method under the four

TABLE V
ACCURACY COMPARISON FOR SUBJECT-INDEPENDENT EXPERIMENTS WITH ORIGINAL AND PROPOSED METHODS UNDER FOUR DIFFERENT CLASSIFIERS

Subject	Methods	KNN	DT	NN	SVM
Others → S1	Original	50.45	46.16	65.41	61.11
	Proposed	78.78	74.24	87.00	91.48
Others → S2	Original	59.28	53.80	69.88	69.75
	Proposed	79.40	60.93	83.36	84.81
Others → S3	Original	73.03	61.12	75.25	76.54
	Proposed	89.77	92.52	91.99	92.96
Others → S4	Original	87.24	74.53	94.31	92.59
	Proposed	94.55	92.59	97.63	100
Others → S5	Original	68.20	35.30	63.65	68.52
	Proposed	87.39	69.70	83.96	82.96
Average	Original	67.64	54.18	73.70	73.70
	Proposed	**85.78**	**78.00**	**88.79**	**90.44**

"Others → S1" means the use of the data from subject 1 for testing, and the remaining data from other subjects for training.

classifiers, comparing with the method using the original data. This is because our proposed method eliminates the effect of orientation variations caused by different clothing and body shape among different subjects. The overall recognition accuracy is slightly worse than that of orientation-independent experiments, because different behavior among subjects contains different signal patterns which are unpredictable. This degradation of accuracy can be resolved by using the online learning method which will be introduced in the next section. Another observation is that the experiment of "Others → S4" achieves 100% with the SVM algorithm, which indicates that the behavior of subject 4 is universal. Among all the classification algorithms, the SVM algorithm with the proposed CT-PCA scheme outperforms the other classifiers on average results, which is consistent with the conclusions in orientation-independent and placement-independent experiments.

G. Online Learning Results

Since the SVM algorithm performs the best in the previous experiments, we leverage on an efficient OISVM algorithm to enhance the system performance on placement-independent and subject-independent experiments. We choose a small portion of the data from the unseen placement or subject for updating of SVM and the rest for testing. Instead of retrain SVM using the newly available data, which is time consuming, we online update the parameters of the existing SVM algorithm trained offline with previously available data to enhance the performance of the algorithm.

Fig. 6 shows the results of OISVM on placement-independent experiments with increasing the proportion of data from the unseen placement for updating the parameters of the algorithm. The overall trend of detection accuracy represented by the average results in Fig. 6 increases with the increase of data from the unseen placement. The final accuracy with 50% of data from the new placement achieves 88.74% which is almost 10% improvement over the offline approach without online updating.

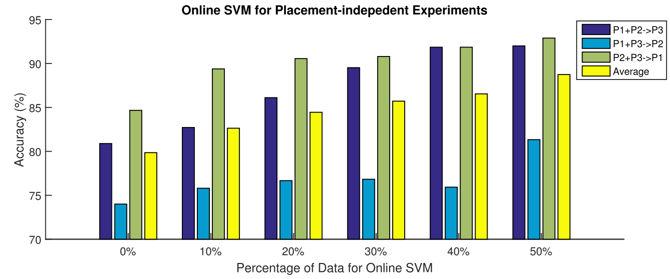

Fig. 6. Results of OISVM on placement-independent experiments with different percentage of data from unseen placement.

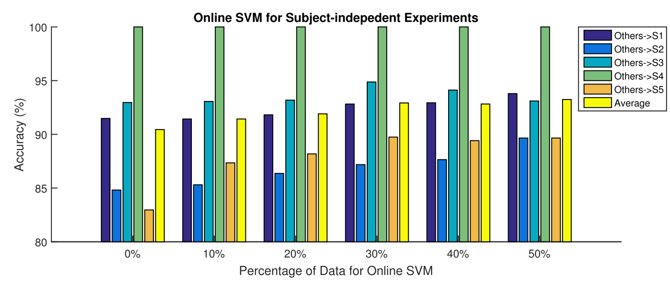

Fig. 7. Results of OISVM on subject-independent experiments with different percentage of data from unseen subject.

For the experiment of "P1+P3 → P2," the detection accuracy slightly decreases with 40% of data from the new placement for updating compared with that of 30%. This can be caused by the limited data size and the random noise in the data. Thus, one of our future works is to collect more data for model construction.

Fig. 7 demonstrates the results of OISVM on subject-independent experiments with increasing the proportion of data from the unseen subject. The overall accuracy represented by the average results slowly increases with the increasing of the percentage of data from the unseen subject. However, the experiment of "Others → S3" slightly decreases when the percentage of data is larger than 30%, which may be caused by the limited data size left for testing and the random noise in the data. Due to the generic behavior of Subject 4, the experiment of "Others → S4" has already achieved 100% in subject-independent experiment (see Table V). Thus, the detection accuracy of increasing data from this unseen subject will always be 100%. Since subject variations have lower influence on the system performance compared to placement variations based on the observations of Tables IV and V, the OISVM algorithm has smaller improvements on subject-independent experiments.

V. CONCLUSION AND FUTURE WORKS

In this paper, we proposed a robust human activity recognition system using smartphone sensors considering orientation, placement, and subject variations. A CT-PCA scheme was proposed to eliminate the effect of orientation variations. Orientation-independent experiments have shown the effectiveness of this proposed scheme compared with the state-of-the-art methods. The proposed scheme also showed impressive improvements on placement-independent and subject-independent experiments, because different placement and subject contains orientation variations which can be eliminated by the proposed CT-PCA method. However, some inherent difference of signals for different placement and subject deteriorates the recognition performance of the system. Thus, we leveraged on an efficient OISVM algorithm for placement-independent and subject-independent experiments. The experimental results demonstrated the effectiveness of this approach, especially on placement-independent experiments which were presented to have a low recognition accuracy.

In future works, we attempt to collect more data from more subjects with different living behavior, aging, gender, etc., and more placements for model construction. Feature extraction and selection are also crucial for activity recognition. We shall explore more representative features and more efficient feature selection methods. Some recent works applied deep NN for feature learning [14], [33], which can be an interesting field to explore. Another future work is that we intend to directly realize the online learning process instead of simulation. To achieve that, one possible way is to upload small amount of labeled data from the new placement or subject to the cloud through Wi-Fi, and then, the online algorithm can be running on the cloud to online update the parameters.

With the developed activity recognition system, we can monitor the elders and evaluate their activity level for healthcare services. Moreover, the smart building research whose ultimate goal is to create a comfortable indoor environment with less energy consumption is a hot topic. The recognized human activity can be used to determine the thermal comfort level of users with some other parameters [39]. Based on the thermal comfort level of each occupant, various control algorithms can be utilized to create an environment with high human comfort and low energy consumption.

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