Classifying Daily Activities regardless of Wearable Motion Sensor Orientation

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***Abstract*—Most studies on wearable sensing assume that each sensor is correctly placed on the body, fixed to a pre-determined position at a pre-determined orientation. This is not practical and feasible in many applications where elderly, disabled, or injured people need to place the sensor units on their own, especially for wireless and small sensor units. It is a considerable improvement to make wearable systems robust against the placement orientations of the sensors, and further, to allow the sensors to be placed at any orientation. For this purpose, we propose a transformation based on Singular Value Decomposition (SVD) that removes the absolute orientation information from the sensor data. We apply this transformation in the pre-processing stage of the standard human activity recognition scheme using multiple publicly available datasets, classifiers, and cross-validation techniques, and achieve an average accuracy that is only 7.56 % lower than the reference approach with fixed sensor orientations. The most common method that is an alternative to the proposed transformation is taking the Euclidean norm of 3D data vectors, which obtains 13.50 % lower accuracy than the reference approach. We show that randomly oriented sensors cause a reduction of 21.21 % in the activity recognition accuracy when no transformation is applied for orientation invariance; hence, the standard system cannot handle incorrectly oriented sensors. On the other hand, the proposed approach allows users to place the sensor units at any orientation on their body with an acceptable reduction in the accuracy, outperforming the common Euclidean norm approach.**

***Keywords*–Human activity recognition; Wearable sensing; Orientation-invariant sensing; Motion sensors; Singular value decomposition.**

I. INTRODUCTION

The exceptional development of mobile devices and their sensing capabilities have enabled them to seamlessly obtain information about people's activities and behaviors. Human activity recognition finds application in the human-computer interaction, healthcare, surveillance, military, and entertainment domains [1]. There are mainly two approaches in activity recognition: wearable sensing and computer vision. As a result of increased computational power and reduced size and weight of mobile devices, wearable sensing has become applicable to various scenarios in a less obtrusive manner, whereas the vision-based approach requires external cameras that reduce the mobility of the subject and raise privacy concerns [2].

In wearable sensing applications including human activity recognition, it is often assumed that each wearable device that contains sensors is placed at a pre-determined position on the body at a pre-determined orientation. Wearable devices have reduced in size and gained wireless communication capabilities; hence, they have become more likely to be incorrectly placed on the body. For instance, smart phones can be carried in a pocket at different orientations, and it is obtrusive to require the user to place his/her phone in his/her pocket always at a fixed orientation. Moreover, in some applications, these sensors are used by elderly, disabled, injured people, or children who may have difficulty in determining the orientation of the sensors for correct placement. However, while there are many studies on activity recognition using wearable motion sensors, only a small fraction of them considers incorrectly orientated sensors [3].

Inertial sensors (accelerometers and gyroscopes) and magnetometers are the common types of wearable motion sensors. Each sensor is typically tri-axial, acquiring data on three mutually perpendicular axes that are part of the device. When the sensor is placed at the same position at a different orientation, the acquired data have a representation in a new, rotated coordinate frame. Wearable systems that assume correct sensor placement are not robust against this change in general. We propose a transformation that removes the dependency of the data on the sensor axes while keeping most of the information content of the data. In this approach, the transformed data are invariant to the orientation at which the sensors are placed on the body, which enables the users to place the sensor units at any orientation at the pre-determined positions.

The rest of this paper is organized as follows: We summarize the related work in Section II. The proposed method for orientation invariance is described in Section III. Section IV includes the description of the datasets, the activity recognition scheme, and the experimental results. In Section V, the proposed method is discussed comparatively with the existing approaches. We state our conclusions and directions for future work in Section VI.

II. RELATED WORK

The most common and the simplest approach in the literature to achieve robustness to incorrectly oriented sensors is to take the Euclidean norm (that is, the magnitude) of the 3D vectors acquired by tri-axial sensors. The Euclidean norm of the acquired vectors does not depend on the orientation of the sensor. References [4]–[7] use the magnitude in classification, whereas [1][8][9] append the magnitude to the tri-axial sensor data as a fourth axis.

The second approach assumes that the gravity component is dominant over the linear acceleration component in the acceleration vectors during daily activities, and estimates this direction by averaging the accelerometer data [10]–[13]. Then, the tri-axial vectors are decomposed into vertical and horizontal components [10]–[12]. Reference [13] additionally calculates the forward-backward direction of the body as the principal axis that is perpendicular to the vertical axis.

In our earlier work [14], we proposed two alternative transformations to remove the information regarding absolute sensor orientation without making any assumptions about the sensor configurations or usage scenario. The first transformation extracts geometrical features from tri-axial sensor data, whereas the second projects the sensor data onto three principal axes in each time segment. Both transformations are shown to significantly improve the activity recognition accuracy when the sensors are randomly oriented. Reference [15] applies Principal Component Analysis (PCA) to the tri-axial data to remove the information related to absolute sensor orientation.

Another approach is to estimate the sensor orientation relative to the Earth frame, based on accelerometer, gyroscope, and magnetometer data [16]. Then, the sensor readings can be represented in the fixed Earth frame, independent of the sensor orientation.

Reference [17] classifies the orientation of the sensor unit among four pre-determined orientations based on the acquired data while the unit is moving and rotates the sensor data accordingly. Reference [18] assumes that incorrect placement of a sensor unit only affects the class means in the feature space, which may not be always true, and compensates for this by using the expectation-maximization algorithm. In [19], orientation invariance is achieved based on calibration postures that the subjects need to perform after placing the sensor units. Reference [20] develops a robust classification methodology against corruption in some portion of the data to handle incorrect placement of some of the sensor units.

III. Proposed Transformation for Orientation Invariance

The tri-axial sensor data are originally acquired in the sensor coordinate frame in terms of the x, y, z axes that depend on the orientation at which the sensor is fixed on the body. To achieve orientation invariance, we apply SVD to the data to represent them in terms of the principal axes.

The sensor data acquired in a time segment can be represented as a matrix

$$\mathbf{A} = [\mathbf{a}_1 \ \mathbf{a}_2 \ \cdots \ \mathbf{a}_N] \tag{1}$$

where $\mathbf{a}_i = [a_{ix} \ a_{iy} \ a_{iz}]^\mathsf{T} \quad (i = 1, \ldots, N)$ is the acquired data vector in 3D space at time sample i. We decompose $\mathbf{A}$ into three matrices by SVD as

$$\mathbf{A} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^\mathsf{T} \tag{2}$$

In the compact form, $\boldsymbol{\Sigma}$ is a $3{\times}3$ diagonal matrix containing the singular values of $\mathbf{A}$. The 3×3 and $3 \times N$ matrices $\mathbf{U}$ and $\mathbf{V}$ contain the left and right singular vectors in their columns, respectively. Since $\mathbf{A}$ consists of real numbers, $\mathbf{U}$ and $\mathbf{V}$ have orthonormal columns and satisfy $\mathbf{U}\mathbf{U}^\mathsf{T} = \mathbf{U}^\mathsf{T}\mathbf{U} = \mathbf{I}_{3\times3}$ and $\mathbf{V}^\mathsf{T}\mathbf{V} = \mathbf{I}_{N\times N}$.

Placing the sensor unit at a different orientation is equivalent to applying the same rotation to all the data vectors in 3D space, provided that the sensor unit is rigidly attached to the body. Here, we assume that the sensor unit moves together with the body part it is placed on, regardless of the orientation at which it is fixed on the body. This assumption is implicitly made in almost all studies on orientation invariance because otherwise the sensor unit would rotate independently of the body and would not be able to capture substantial information about the body motion.

A different orientation of the sensor causes each of the acquired data vectors $\mathbf{a}_i$ to be rotated by the same (unknown) rotation matrix $\mathbf{R}$ as $\tilde{\mathbf{a}}_i = \mathbf{R}\mathbf{a}_i$, which can be represented as the matrix product $\tilde{\mathbf{A}} = \mathbf{R}\mathbf{A}$. Using (2), the rotated data matrix can be expressed as

$$\tilde{\mathbf{A}} = \mathbf{R}\left(\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^\mathsf{T}\right) = (\mathbf{R}\mathbf{U})\,\boldsymbol{\Sigma}\mathbf{V}^\mathsf{T} = \tilde{\mathbf{U}}\boldsymbol{\Sigma}\mathbf{V}^\mathsf{T} \tag{3}$$

The last term corresponds to the SVD of $\tilde{\mathbf{A}}$ with a new left singular matrix, $\tilde{\mathbf{U}} = \mathbf{R}\mathbf{U}$, because the SVD representation is unique (up to the signs of the principal vectors [21]) and $\tilde{\mathbf{U}}$ is also an orthonormal matrix that satisfies the properties

$$\begin{aligned} \tilde{\mathbf{U}}\tilde{\mathbf{U}}^\mathsf{T} &= (\mathbf{R}\mathbf{U})(\mathbf{R}\mathbf{U})^\mathsf{T} = \mathbf{R}\mathbf{U}\mathbf{U}^\mathsf{T}\mathbf{R}^\mathsf{T} = \mathbf{R}\mathbf{R}^\mathsf{T} = \mathbf{I}_{3\times3} \\ \tilde{\mathbf{U}}^\mathsf{T}\tilde{\mathbf{U}} &= (\mathbf{R}\mathbf{U})^\mathsf{T}(\mathbf{R}\mathbf{U}) = \mathbf{U}^\mathsf{T}\mathbf{R}^\mathsf{T}\mathbf{R}\mathbf{U} = \mathbf{U}^\mathsf{T}\mathbf{U} = \mathbf{I}_{3\times3} \end{aligned} \tag{4}$$

where the $\mathbf{R}$ matrix is orthonormal: $\mathbf{R}^\mathsf{T}\mathbf{R} = \mathbf{R}\mathbf{R}^\mathsf{T} = \mathbf{I}_{3\times3}$.

We observe from (2) and (3) that the matrices $\boldsymbol{\Sigma}$ and $\mathbf{V}$ remain the same when $\mathbf{A}$ is rotated. Hence, the matrix product

$$\mathbf{B} \triangleq \boldsymbol{\Sigma}\mathbf{V}^\mathsf{T} \tag{5}$$

is taken as the transformed data that are invariant to the orientation at which the sensor is placed on the body.

This transformation is indeed equivalent to a rotation by $\mathbf{U}^\mathsf{T}$ (which may be left or right handed) because $\mathbf{U}^\mathsf{T}\mathbf{A} = \mathbf{U}^\mathsf{T}\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^\mathsf{T} = \boldsymbol{\Sigma}\mathbf{V}^\mathsf{T} = \mathbf{B}$. In this way, the data, which are originally in terms of the x, y, z axes of the sensor frame, are represented in terms of three orthogonal principal axes $\mathbf{u}_1$, $\mathbf{u}_2$, $\mathbf{u}_3$ that are the columns of $\mathbf{U}$.

If a sensor unit contains multiple types of tri-axial sensors such as an accelerometer and a gyroscope, a joint transformation can be calculated for all the sensors because they are exposed to the same rotation. To calculate a joint SVD, the $\mathbf{A}$ matrices acquired from multiple sensors can be concatenated horizontally. To transform the data, each data matrix is pre-multiplied by the transpose of the left singular matrix $\mathbf{U}$ of the joint SVD.

The original sensor data $\mathbf{A}$, the randomly rotated data $\tilde{\mathbf{A}}$, and the transformed data $\mathbf{B}$ are plotted in Figure 1 for the walking activity performed by subject 1 in dataset D_4. Note that $\mathbf{B}$ can be obtained by applying the proposed transformation to either $\mathbf{A}$ or $\tilde{\mathbf{A}}$. We observe that the periodic nature of the walking activity is preserved in the transformed signal.

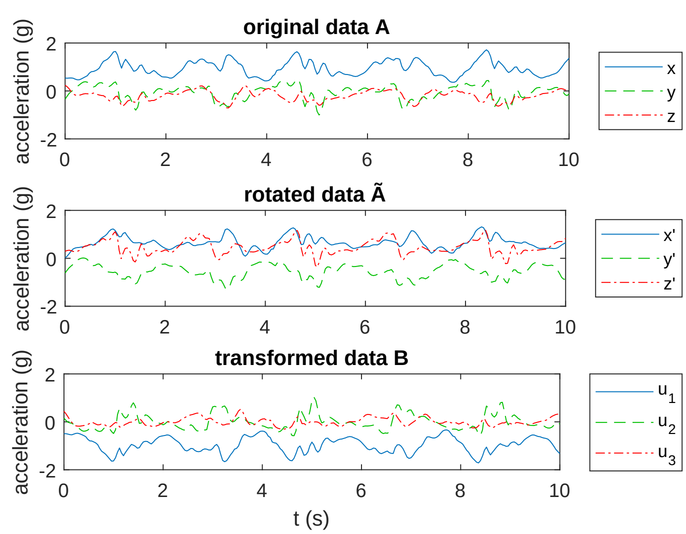


Figure 1. The original, rotated, and transformed sensor data.

TABLE I. ATTRIBUTES OF THE FIVE DATASETS.

dataset	$\mathbf{D}_1$ [22]	$\mathbf{D}_2$ [23]	$\mathbf{D}_3$ [24]	$\mathbf{D}_4$ [25]	$\mathbf{D}_5$ [26]
no. of subjects	8	4	30	14	15
no. of activities	19	5	6	12	7
activities (*: stationary activity)	(1*) sitting, (2*) standing, (3*,4*) lying on back and on right side, (5,6) ascending and descending stairs, (7) standing still in an elevator, (8) moving around in an elevator, (9) walking in a parking lot, (10,11) walking on a treadmill in flat and 15° inclined positions at a speed of 4 km/h, (12) running on a treadmill at a speed of 8 km/h, (13) exercising on a stepper, (14) exercising on a cross trainer, (15,16) cycling on an exercise bike in horizontal and vertical positions, (17) rowing, (18) jumping, (19) playing basketball	(1) sitting down, (2) standing up, (3*) standing, (4) walking, (5*) sitting	(1) walking, (2) ascending stairs, (3) descending stairs, (4*) sitting, (5*) standing, (6*) lying	(1) walking, (2,3) walking left and right, (4,5) ascending and descending stairs, (6) running forward, (7) jumping, (8*) sitting, (9*) standing, (10*) sleeping, (11,12) ascending and descending in an elevator	(1*) working at a computer, (2) standing up–walking–ascending/ descending stairs, (3*) standing, (4) walking, (5) ascending/descending stairs, (6) walking and talking with someone, (7*) talking while standing
no. of units	5	4	1	1	1
no. of axes per unit	9	3	6	6	3
unit positions	torso, right and left arm, right and left leg	waist, left thigh, right ankle, right upper arm	waist	front right hip	chest
sensor types	accelerometer, gyroscope, magnetometer	accelerometer	accelerometer, gyroscope	accelerometer, gyroscope	accelerometer
dataset duration (hr)	13	8	7	7	10
sampling rate (Hz)	25	8	50	100	52
no. of time segments	9,120	4,130	10,299	5,353	7,345
segment duration (s)	5	5	2.56	5	5
no. of features (with no transformation)	1,170	276	234	156	78

IV. Experimental Methodology and Results

To assess the performance of the proposed method, we apply the standard activity recognition scheme on multiple datasets, classifiers, and cross-validation techniques.

A. Datasets

We use five publicly available datasets, which have different sensor configurations and have been acquired by different research groups [22]–[26]. Brief information about the datasets is provided in Table I.

B. Pre-Processing

The time-domain data are divided into segments of fixed duration (see Table I). Then, we apply one of the following pre-processing methods:

- **REF (Reference):** No transformation is applied.
- **ROT (Random Rotation):** The tri-axial data acquired from each sensor unit in each time segment are rotated by a different random rotation matrix generated from independently and uniformly distributed roll, pitch, and yaw angles [27] in the interval $[0, 2\pi)$.
- **NORM (Euclidean Norm):** The Euclidean norm of each 3D data vector is taken. This is an existing approach for orientation invariance [4]–[7] and included for comparison.
- **SVDT (SVD-based Transformation):** We apply the proposed transformation defined in Section III to each sensor unit in each time segment separately. This method is robust against placing each sensor unit at a different orientation in each time segment.

C. Classification

After transforming the time-domain data, the following statistical features are extracted from each axis of each time segment: minimum, maximum, mean, variance, skewness, kurtosis, the coefficients of the autocorrelation sequence for the lag values of $5, 10, \ldots, 50$ samples, and the five largest Discrete Fourier Transform (DFT) peaks (that are at least 11 samples apart) with the corresponding frequencies. Fewer autocorrelation coefficients and DFT peaks can be used in some datasets if there are not sufficiently many time samples in a segment. The number of features extracted from a single time segment of the untransformed data is provided in the last row of Table I for each dataset.

The features are normalized to the interval $[0, 1]$ for each subject in each dataset. Then, PCA is used to reduce the number of features to 30.

Classification is performed by four state-of-the-art classifiers (see [28] for further information):

- **Bayesian Decision Making (BDM):** A multi-variate Gaussian distribution is fitted to the training feature vectors of each class. For a test feature vector, the class that has the highest class-conditional probability is selected.
- **k-Nearest Neighbor (k-NN):** The training phase consists of the storage of the training vectors with their true labels. A test vector is assigned the most common class label among the k training vectors that are closest to it in terms of the Euclidean distance. A suitable value of k is selected as 7.
- **Support Vector Machines (SVM):** The features are mapped to a higher-dimensional space by using the Gaussian Radial Basis Function (RBF). A binary classifier is trained for each distinct class pair to divide the feature space into two regions by a hyperplane that maximizes the margin. The classification relies on the decision of the most confident classifier. The RBF and penalty parameters are optimized as $\gamma = 0.2$ and $C = 40$, respectively, by a two-level grid search [14].
- **Artificial Neural Networks (ANN):** Three layers of neurons with a sigmoid output function are used. The number of neurons in the input and output layers are 30 and as many as the number of classes, respectively. The number of neurons in the intermediate layer is selected as the nearest integer to the average of the optimistic and pessimistic cases [14]. Coefficients of the linear combinations are randomly initialized in $[0, 0.2]$ and determined by the back-propagation algorithm with an adaptive stopping criterion [14] and a learning rate of 0.3. In classification, the test vector is fed to the input and the class corresponding to the maximum output is selected.

Two cross-validation techniques are used to assess the accuracy: P-fold (with $P = 10$) randomly divides the feature vectors into P partitions and tests each partition by a classifier trained by the feature vectors in the remaining partitions. Leave-1-subject-Out (L1O) considers each subject's data as a partition and follows the same approach as P-fold. L1O is more challenging and generalizable than P-fold because the training and test vectors belong to different subjects in L1O.

D. Results

The accuracies for all the classifiers, pre-processing approaches, and datasets are shown in the bar chart in Figure 2. A stick centered at the tip of each bar indicates plus/minus one standard deviation in the accuracy over the cross-validation iterations. Figures 2(a)–(c) show the results for all the activities, stationary activities, and non-stationary activities, respectively. (Stationary activities are denoted by an asterisk (*) in Table I.) Figure 3 shows the accuracy values averaged over the four classifiers and the five datasets for each approach and cross-validation technique separately for the the whole activity set, stationary, and non-stationary activities.

As observed from Figures 2 and 3, the highest accuracy is obtained by using the REF approach where the orientations of the sensor units are fixed and no transformation is applied to the data. The accuracy considerably drops in the ROT approach where the acquired data are rotated randomly to simulate the placement of the sensor units at random orientations and no transformation is applied for orientation invariance. This shows that the standard activity recognition scheme is not robust against incorrectly oriented sensors. Among the two types of transformations for orientation invariance, the proposed approach SVDT performs significantly better than the widely used approach NORM on the average. This is especially observed for datasets D_1 and D_4 and for non-stationary activities.

V. Discussion

We consider different approaches at the pre-processing stage to observe the effects of incorrectly oriented sensors and the transformations for orientation invariance, unlike most of the existing studies. The sensor units are correctly placed on the body in all the datasets that we use, and we synthetically rotate the signals to simulate randomly oriented sensors. This enables us to use the same data in both approaches so that we can fairly compare them. If a new dataset were recorded for randomly rotated sensors, it would have a different level of difficulty in activity recognition because of the variations that occur in the data. These variations can be observed from the standard deviations over the cross-validation iterations in Figure 2. Reference [29] investigates the variations in the activity data within and between subjects in detail.

When we apply the existing or the proposed transformation to the sensor data, we mathematically ensure that the transformed data are not affected by the orientations at which the sensors are fixed to the body. In other words, the same data can be obtained by transforming the original and randomly rotated data (up to the signs of the axes in SVDT). Therefore, we do not need to record a new dataset with different sensor orientations to observe the effects of the orientation-invariant transformations on the activity recognition accuracy.

In the ROT approach, we rotate the tri-axial sensor data separately for each sensor unit in each time segment. Hence, the training and test sets contain data corresponding to different sensor orientations. This is advantageous for the system because in the training phase, the classifiers may adapt to the variation in the data by relying on (the linear combinations of) the features that are more robust against the changes in sensor orientations. Keeping the training data unchanged and rotating only the test data may result in a higher accuracy compared to the method we use.

In Section III, we allow the user to initially place the sensors on his/her body at any orientation, but we assume that the sensor rotates together with the body part on which it is placed; that is, the sensor is rigidly attached to the body. This assumption is required even for the simplest approach, NORM, because otherwise the motion sensors would record different signals when they rotate freely independent of the body movements. In particular, the gravity vector acquired by the accelerometer, the angular rate detected by the gyroscope, and the magnetic field of the Earth measured by the magnetometer would be all unrelated to the body motion in this case.

A sudden change in the orientation of the sensor with respect to the body corrupts the signals for a short time interval. If the data are transformed by the NORM approach, the same, short time interval will be corrupted in the transformed data. If the proposed transformation SVDT is applied, different principal vectors will be obtained, and the whole transformed data will be affected. Since we transform each time segment separately, only the corresponding segment(s) will be affected, which corresponds to a short time interval because the segments have a duration of at most 5 seconds.

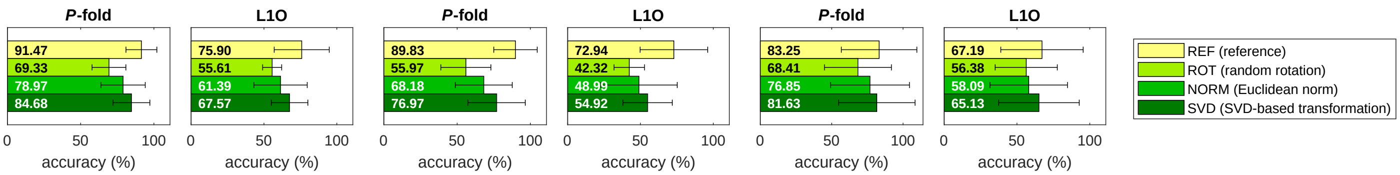
There is an important advantage of the method we propose over most of the existing approaches: Our method only requires a transformation to be added at the pre-processing stage, without a need to modify the rest of the activity recognition system. The input and output of the transformation are both tri-axial and of the same form. The transformation does not change the physical units of the acquired data and their dimensionality; hence, does not require any modifications in the following steps in the activity recognition paradigm.

VI. Conclusions and Future Work

In wearable sensing, it is mostly assumed that the sensors are placed on the body at fixed orientations, which is not feasible in many applications such as monitoring of the elderly or children. We show that incorrectly oriented wearable sensors significantly decrease the activity recognition accuracy, which is consistently valid for multiple datasets, classifiers, and cross-validation tests. We propose an SVD-based transformation to represent the tri-axial data in terms of three principal axes to remove the information of absolute sensor orientation. In most cases, this method significantly increases the accuracy when the sensors are placed at random orientations, providing an accuracy close to the reference approach with fixed sensor orientations in some cases. Our approach achieves a better overall accuracy than the conventional Euclidean norm method and can be integrated into most of the existing systems without much effort.

As future work, the proposed method can be applied to other applications of wearable sensing, such as fall detection [30] and physical therapy [31], and extended to handle the incorrect positions of the sensor units in addition to incorrect orientations.

Figure 2. Activity recognition accuracy of each classifier for each pre-processing approach for each dataset. The horizontal stick centered at the tip of each bar indicates plus/minus one standard deviation in the accuracy over the cross-validation iterations.



(a) all activities (b) stationary activities (c) non-stationary activities

Figure 3. Activity recognition accuracy averaged over the classifiers and the datasets for each pre-processing approach. The horizontal stick centered at the tip of each bar indicates plus/minus one standard deviation in the accuracy over the classifiers and the datasets.

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