Automatic detection of unbalanced sitting postures in wheelchairs using unlabeled sensor data

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Abstract—This letter presents an effective data-driven anomaly detection scheme for automatically recognizing unbalanced sitting posture in a wheelchair using data from pressure sensors embedded in the wheelchair. Essentially, the designed approach merges the desirable features of the kernel principal components analysis (KPCA) as a feature extractor with the Kantorovich Distance (KD)-driven monitoring chart to detect abnormal sitting posture in a wheelchair. It is worth noting that this approach does not require labeled data and only employs normal events data to train the detection model, which makes it more appealing in practice. Specifically, we used the KPCA model to exploit its capacity to reduce the dimensionality of nonlinear data to obtain good detection. At the same time, the KD monitoring scheme is an efficient distribution-driven anomaly detection approach in multivariate data. Furthermore, a nonparametric decision threshold using kernel density estimation is adopted to extend the flexibility of the proposed approach. Publically available data has been used to verify the detection capacity of the proposed approach. The overall detection system proved promising, outperforming some commonly used monitoring methods.

Index Terms—Data-driven, kernel principal components analysis, posture detection, non-parametric threshold.

I. INTRODUCTION

Wheelchair users have increased during the last decades because of several factors, such as traffic accidents, falls, and violence [1]. Approximately 1.85% of the world’s population needs a wheelchair, as the WHO World Report on Disability and wheelchair foundation pointed out. The use of wheelchairs for persons with disabilities could improve their access to mobility, social inclusion, and community participation [2]. However, unbalanced sitting postures in a wheelchair can negatively affect the health condition of wheelchair users. Specifically, incorrect posture in a wheelchair causes chronic pain, sclerosis, kyphosis, skin and respiratory problems, loss of brain skills, and physical health problems, such as muscle rigidity, fatigue, and muscle pain [3] Alternatively, adequate sitting in the wheelchair can decrease pain intensity, and the possibility of ulcers formation [4]. Thus, monitoring sitting posture in a wheelchair is necessary to avoid improper postures.

Over the last decade, there has been increasing interest in developing advanced methods to improve users’ wheelchair comfort [2]. For instance, in [5], Mohamed et al. investigated the influence of whole-body vibration on powered wheelchair (EPW) users based on the ISO-2631 standard. To this end, experiments have been conducted by four EPW users under different terrain surfaces (e.g., pavement bricks and tiled concrete). Results reveal the influence of users’ weights and terrain surfaces on vibration perception. They highlighted that the health risk of lightweight users increased compared to heavyweight users because heavyweight users could dampen low vibration. In [6], a supervised approach using principal component analysis (PCA) as a feature extractor and the k-nearest neighbors (KNN) classifier for posture recognition in conventional chairs. This approach reached a classification accuracy of 75% since PCA is suitable only for Gaussian data; however, the data collected from the sensors embedded in the chair are non-gaussian, which leads to miss-classification results. Recently in [7], a supervised machine learning approach has been introduced to identify a person’s posture based on sensor network embedded in the wheelchair. This approach used the Condensed Nearest-Neighbours approach for data filtering, the Kennard-Stone algorithm to balance the data, PCA for dimensionality reduction, and KNN algorithm for posture classification. Results indicated that this combined approach achieved an average accuracy of over 75%. This could be due to the small-sized and unlabeled data used in this study. Most of the developed detection schemes for sitting posture recognition are generally designed using shallow supervised techniques that need labeled data in training. However, getting labeled data is not obvious and is time-consuming. Thus, this study aims to design a semi-supervised data-driven detector for sitting posture monitoring that does not require labeled data.

Accurate recognition of sitting posture is vital to enhance wheelchair users’ comfort and health monitoring. This letter introduces an innovative approach for sitting posture recognition for wheelchair users using unlabeled data. Importantly, the proposed technique integrates the benefits of kernel PCA (KPCA) model as a residual generator with the Kantorovich Distance (KD)-driven monitoring chart to sense abnormal sitting posture in a wheelchair. The key characteristic of the KPCA-KD anomaly detection scheme is its capacity to uncover anomalies without considering labeled data. At first, the KPCA-based KD detector is constructed based on training data (normal sitting posture) and then used to detect potential abnormal sitting postures. KPCA is an efficient model for extracting useful information in nonlinear data. Furthermore, Kernel density estimation (KDE) is employed to compute non-parametric...
thresholds for KPCA-KD approach. The KD monitoring chart is applied to the residuals obtained from KPCA for anomaly detection. We assessed the effectiveness of this approach by using experimental data provided in [7] for sitting posture recognition for wheelchair users. Moreover, we compared the detection performance of the proposed scheme to that of the traditional PCA and KPCA monitoring techniques. Results demonstrated the superior detection performance of unbalanced posture sitting using the proposed KPCA-KD approach.

II. METHODOLOGY

This section presents the materials needed to design the proposed KPCA-DK approach: the KPCA and the KD techniques.

A. Kernel PCA

KPCA is a multivariate technique that is focused on extracting non-linear features from the data through the use of non-linear kernel functions. The KPCA technique performs projection of data to a higher dimensional feature space where the data is linearly separable [8]. For a given sensor data \(X \in \mathbb{R}^{n \times d}\) with \(n\) observations and \(d\) variables, the data is transferred to linear feature space \(\mathbb{R}^{d'}\) and the corresponding covariance matrix can be computed as [9]:

\[
\Sigma^F = \frac{1}{n} \sum_{j=1}^{n} \Psi(x_j)\Psi(x_j)^T, \tag{1}
\]

where \(\Psi(.)\) is the mapping function. The problem \(\lambda v = \Sigma^F v\) is solved and below expression is obtained by introducing kernel function \(K\):

\[
\sum = \frac{1}{n} \text{K}a \tag{2}
\]

where \(a = [a_1, a_2, ..., a_d]^T\). Next, kernel PCs are computed:

\[
t_k = \langle v_k, \Psi(x) \rangle = \sum_{j=1}^{n} a_j \langle \Psi(x_j)\Psi(x) \rangle \tag{3}
\]

Once KPCA model is developed, it can detect abnormalities in the new data using \(T^2\) and squared prediction error (SPE) based statistical indicators. The variations in model is computed as follows [10]:

\[
T^2 = [t_1, t_2, ..., t_p]\Lambda^{-1}[t_1, t_2, ..., t_p]^T, \tag{4}
\]

\[
SPE = ||\Psi(x) - \Psi(p(x))||^2, \tag{5}
\]

where \(\Lambda^{-1}\) is the diagonal matrix of inverse of eigenvalues associated with retained PCs and \(\Psi(p(x))\) corresponds to first \(p\) PCs in reconstructed feature space. Any abnormality is declared when the value of \(T^2\) and SPE based indicator exceeds a reference threshold. For more details about KPCA-driven monitoring approach, see [10].

B. Kantorovitch distance

KD is a statistical index that has been used in abnormality detection problems in the recent years. The KD statistic refers to the task of transporting information from one distribution to the other relative to a cost function. The cost of transportation is very minimum for transporting information from one distribution to the other relative. This attractive feature has enabled it to be applied in anomaly identification problems. In anomaly identification problems, the KD statistic is computed between the residuals of normal data and the faulty data and then, it is compared with reference threshold. The threshold for KD statistic is calculated using the KDE approach. Specifically, the non-parametric KD threshold is computed by taking \((1-\alpha)^{th}\) quantile of the estimated distribution of residuals, where, \(\alpha\) refers to the probability of false alarm.

C. The wheelchair user’s posture monitoring scheme

A novel technique that integrates KPCA model with the KD metric is proposed to identify improper sitting postures in this work. This approach is performed in four steps as shown in Figure 1:

- The proper posture data is processed and KPCA model is developed using equations (1) (2) and (3).
- The residuals are generated from the model using the equation (7) and the KD detection threshold is evaluated.
- The abnormal sitting data is processed and residuals are generated from developed model using equation (7).
- The KD metric is evaluated between residuals of normal and abnormal sitting data using equation (6) and decision is taken.

![Fig. 1. The proposed KPCA-based KD monitoring strategy.](Image)

III. RESULTS AND DISCUSSION

A. Data description

This study evaluates proposed schemes via actual data from a publicly available database provided in [7], [12]. The data are gathered using HC-SR04 ultrasonic ranging sensors (https://www.sparkfun.com/products/15569) and pressure sensors (https://www.sparkfun.com/products/9375). As shown in Figure 2, there are three sensors on seating (S1, S2, S3) and one ultrasound sensor on backrest (S4). The ultrasonic sensor is employed to measure the distance separating backrest and wheelchair back [7], [12].

To evaluate the performance of the proposed monitoring schemes, we used actual data with 308 data points from the four sensors. More specifically, this data contains 88 samples gathered under correct sitting posture, 100 samples under higher pressure on the backrest and wheelchair back [7], [12].

where \(\mu_c\) and \(\mu_d\) indicate means while \(\Sigma_c\) and \(\Sigma_d\) indicate covariance matrices. The KD statistic is computed between the two distributions using segmentation process which enables it to capture the sensitive details in both data that eventually aids in better detection ability sets [11]. This attractive feature has enabled it to be applied in anomaly identification problems. In anomaly identification problems, the KD statistic is calculated using the KDE approach. Specifically, the non-parametric KD threshold is computed by taking \((1-\alpha)^{th}\) quantile of the estimated distribution of residuals, where, \(\alpha\) refers to the probability of false alarm.
right side, 20 samples under higher pressure on the left side, and 100 samples under higher forward pressure. For more details on this data, see [7]. To visually check the distribution of the used pressure data, the probability density function of the pressure data has been estimated via the kernel density estimation (Figure 3).

Fig. 3. Distribution of the considered pressure variables.

It can be seen from Figure 3 that data are non-Gaussian distributed. It would challenge traditional dimensionality reduction techniques, such as PCA, designed based on the Gaussian assumption of input data. In addition, decision thresholds in conventional monitoring charts, such as $T^2$, are designed based on the Gaussian assumption of data. Thus, the use of KDE to nonparametrically compute the decision threshold in the KPCA-KD chart could be promising.

B. Monitoring results

This section presents the performance of the KPCA-KD scheme in detecting three improper sitting postures on the wheelchair. The abnormal scenarios include position 2, which corresponds to pressure applied on right side of the body (Case 1); position 3, which indicates pressure applied on left side of the body (Case 2) and position 4, which indicates pressure in the forward direction (Case 3). Comparison is carried with PCA-KD, PCA-$T^2$, PCA-SPE, KPCA-$T^2$, and KPCA-SPE-based schemes. The PCA and KPCA models initially undergo training using the normally operating data points, and three optimum PCs are selected in each case. The developed models are then used to detect three abnormal sitting postures on the wheelchair. Five statistical scores commonly used in the literature are adopted to verify the detection performance of the investigated methods: anomaly detection rate (ADR), false alarm rate (FAR), Precision, Recall, and F1-Score. For a binary detection task, the number of true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN) are employed to compute the evaluation metrics.

\[
\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \quad (8)
\]

\[
\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad (9)
\]

\[
F1 - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}}. \quad (10)
\]

The monitoring capability of PCA and KPCA anomaly detection schemes in identifying the three abnormal scenarios is presented in Table 1. For case 1, abnormal sitting position, it can be observed from the table that all anomaly detection methods demonstrate satisfactory performance. The PCA-KD and KPCA-KD-based schemes have improved detection with high ADR and without false alarms, thus, over-performing the conventional anomaly indicators of PCA and KPCA strategy. The performance of PCA and KPCA-based methods in monitoring the case 2 abnormal sitting posture is presented in Figure 4 and Figure 5, respectively. The PCA-$T^2$, PCA-SPE, PCA-KD, KPCA-$T^2$ and KPCA-SPE based strategies detect the abnormal sitting posture but miss at few samples, due to which the ADR value is affected. The ADR values for PCA-$T^2$, PCA-SPE, PCA-KD, KPCA-$T^2$ and KPCA-SPE based strategies are found to be 95.00%, 60.00%, 70.00%, 96.25% and 73.75% respectively. In contrast, the proposed KPCA-KD scheme detects the improper sitting posture with an ADR value of 100.00%.

<table>
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<th>No.</th>
<th>Index</th>
<th>$T^2$</th>
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Next, the PCA-SPE, PCA-KD, and KPCA-KD methods fail to detect case 3 abnormal posture. While the PCA-$T^2$ and KPCA-$T^2$ methods demonstrate fair detection, the KPCA-KD scheme shows good detection with a large ADR value. For all abnormal scenarios, it is observed that the F1-score accuracy is found to be 100%, 100%, and 96.60% for the proposed KPCA-KD scheme, and this is better than other schemes. This could be due to the ability of the KPCA method to capture the non-linear features in multivariate data better than the PCA scheme. Hence, KPCA's anomaly detection is improved. Also, the KD indicator captures sensitive details between...
the residuals of training and testing data, and hence, its performance is superior as compared to $T^2$ and SPE indicators. From all the results, it can be inferred that the proposed KPCA-KD strategy can detect and distinguish three abnormal type of sitting postures for wheelchair users using the unlabeled data.

Despite the enhanced detection performance achieved by the KPCA-KD approach, future works will improve its ability to discriminate different abnormal sitting types. One possible way to alleviate this limitation is to incorporate a classification stage based on a support vector machine or other classifier applied to detected sequences. Another alternative is to apply univariate monitoring charts, such as the generalized likelihood ratio test [13], to the residuals from the KPCA. Furthermore, another direction of improvement consists of using data augmentation techniques to generate large-sized data, which improves the construction of models and thus enhances the detection process.

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