Feature Vector Extraction and Dimensionality Reduction for Wearable Fall Detection: Postprint

Authors: Li Lei, Zhang Fan, Shi Huaji, Zhou Conghua

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Abstract

In wearable fall detection, excessive feature attributes for older adults can cause the curse of dimensionality, affecting subsequent fall detection accuracy. To address this issue, we first employ a time-domain analysis method to extract the initial feature vector set, and then utilize the proposed Improved Kernel Principal Component Analysis algorithm (IKPCA) to perform dimensionality reduction on the feature vectors, thereby obtaining a high-quality feature vector set that yields improved classification performance. The IKPCA algorithm first applies the I-RELIEF algorithm to conduct feature selection on the initial feature vector set, then computes the information measure and similarity measure of fall feature vectors, and finally eliminates invalid fall feature vectors based on their similarity measure. The IKPCA algorithm not only preserves the superior dimensionality reduction capability of the Kernel Principal Component Analysis algorithm (KPCA), but also enhances classification capability. Experiments conducted on real-world datasets demonstrate through comparative analysis that, compared with other algorithms, the IKPCA algorithm can obtain higher-quality feature vector datasets.

Full Text

Preamble

Wearable Fall Detection: Research on Feature Vector Extraction and Dimensionality Reduction

LI Lei, ZHANG Fan, SHI Hua-Ji, ZHOU Conghua
(School of Computer Science & Telecommunication Engineering, Jiangsu University, Zhenjiang, Jiangsu 212013, China)

Abstract: In wearable fall detection for the elderly, an excessive number of characteristic attributes leads to the curse of dimensionality, which adversely affects the accuracy of subsequent fall detection. To address this issue, we first employ time-domain analysis to extract an initial feature vector set, then apply our proposed Improved Kernel Principal Component Analysis (IKPCA) algorithm to reduce the dimensionality of these feature vectors, thereby obtaining a high-quality feature vector set that yields superior classification performance. The IKPCA algorithm initially utilizes the I-RELIEF algorithm for feature selection on the initial feature vector set, then calculates the information measure and similarity measure of fall feature vectors, and finally eliminates invalid fall feature vectors based on their similarity measures.

The IKPCA algorithm not only maintains the excellent dimensionality reduction capability of the Kernel Principal Component Analysis (KPCA) algorithm but also enhances classification performance. Experiments conducted on real datasets demonstrate through comparative analysis that the IKPCA algorithm obtains higher-quality feature vector datasets compared to alternative algorithms.

Keywords: fall detection; feature vector; kernel principal component analysis; dimensionality reduction

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0 Introduction

In wearable fall detection research, the extraction and dimensionality reduction of motion signal feature vectors are closely related to human behavior during falls and the classification algorithms employed, with their effectiveness directly impacting fall detection accuracy. Consequently, feature extraction and dimensionality reduction are critical components in fall detection systems. These processes serve as an intermediate bridge between signal acquisition and fall detection, selecting representative human motion feature vectors from fall detection signals. Their effectiveness profoundly influences detection precision, making the acquisition of more effective feature vectors a persistent research focus.

Existing motion signal feature extraction methods primarily fall into three categories: time-domain analysis, frequency-domain analysis, and time-frequency analysis. Time-domain analysis methods [1-3] extract feature vectors directly from acquired signals. Frequency-domain methods [4-5] first require Fast Fourier Transform processing before feature extraction. Time-frequency analysis [6] employs wavelet transforms for feature extraction. While frequency-domain and time-frequency methods yield more comprehensive feature vectors, their extraction speed is slow, significantly affecting real-time performance. Time-domain analysis, though less comprehensive, offers faster extraction and finds widespread application in embedded devices.

During feature extraction, more feature vectors provide more detailed characterization of fall and daily activities, but simultaneously increase dimensionality, potentially causing the "curse of dimensionality." Therefore, dimensionality reduction of initial feature vectors is necessary to obtain more effective features conducive to fall detection. Dimensionality reduction maps data samples from the original input space to a feature space to reduce dataset dimensions. Principal methods include Principal Component Analysis (PCA) [7-8], Kernel Principal Component Analysis (KPCA) [9], and other nonlinear component analysis techniques. Researchers have also proposed effective dimensionality reduction algorithms: Yang et al. [10] proposed the PCA&MSNR algorithm, demonstrating through gait feature dataset experiments that its reduction performance surpasses both PCA and MSNR; Yang et al. [11] applied FSS and LDA for dimensionality reduction in activity recognition, verifying LDA' s superiority over FSS; Khan et al. [12] proposed the Kernel Discriminant Analysis (KDA) algorithm, validating its feasibility through comparative analysis with LDA; Cheng and Choudhury et al. [13,14] employed AdaBoost for dimensionality reduction with more pronounced effects.

While these algorithms preserve original information, they inadequately consider class information and its maximization, making it uncertain whether effective fall feature vector sets can be obtained after reduction. This paper first extracts an initial feature vector set using time-domain analysis, then applies our proposed Improved KPCA (IKPCA) algorithm for further reduction to obtain a rational and effective feature vector set. Finally, through comparative experiments with datasets and Support Vector Machine (SVM) classification, we verify that our method yields superior feature vector datasets. The IKPCA algorithm first uses the I-RELIEF [15] algorithm for feature selection on the initial fall feature vector set obtained through time-domain analysis, then calculates information and similarity measures, and finally eliminates invalid vectors based on similarity measures. IKPCA maintains KPCA' s dimensionality reduction capability while delivering better classification performance.

This paper selects twelve feature statistics, including mean, standard deviation, skewness, kurtosis, Signal Magnitude Area (SMA), and energy expenditure. From sampling vectors, we calculate 75 features across eight variables to form the initial fall feature vector set, as detailed in and .

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1 Feature Vector Extraction

In wearable fall detection, signals acquired from wearable devices cannot directly form effective datasets for training classifiers, making reasonable fall feature vector extraction essential. Time-domain analysis, a primary method for motion signal processing, extracts target feature vectors directly from temporal signal data. Its extraction speed makes it widely applicable in embedded devices. In fall detection, three-axis accelerometers and three-axis gyroscopes are commonly employed, yielding eight variables per sampling point: three acceleration components, resultant acceleration, three angular velocity components, and resultant angular velocity.

However, time-domain analysis generates excessive feature vector types, potentially causing dimensionality disasters that hinder classifier training. Therefore, further dimensionality reduction is necessary.

2.1 KPCA Algorithm Fundamentals

KPCA is a kernel function-based extension of PCA that maps input space to feature space for PCA implementation. Its key innovation employs nonlinear functions to transform inner product operations in feature space into kernel function calculations in input space, dramatically simplifying computation.

Let $\mathcal{X}$ be the initial feature vector set and Φ denote the mapping from original input space to feature space, where feature space data satisfies centralization requirements. The covariance matrix C is given by:

$$C = \frac{1}{m}\sum_{i=1}^{m}\Phi(x_i)\Phi(x_i)^T$$

Direct computation is challenging but can be solved using kernel functions. For an $m \times m$ kernel matrix K where $K_{ij} = k(x_i, x_j) = \Phi(x_i)^T\Phi(x_j)$, the covariance matrix in feature space becomes $C = \frac{1}{m}K$. If this condition fails, kernel matrix centering adjustment is required:

$$K' = K - \mathbf{1}_m K - K\mathbf{1}_m + \mathbf{1}_m K \mathbf{1}_m$$

where $\mathbf{1}_m$ is an $m \times m$ matrix with all elements equal to $1/m$. Equation (4) then computes eigenvalues λ and eigenvectors v of K', yielding the top n eigenvalues and corresponding eigenvectors. The principal components are obtained through:

$$Y = V^T K'$$

where V contains the eigenvectors. This process constitutes the KPCA algorithm described in Algorithm 1.

Algorithm 1: KPCA Algorithm
Input: Initial feature vector set $\mathcal{X}$, mapping Φ
Output: Resultant feature vector set
a) Compute kernel matrix K using the kernel function
b) Center kernel matrix K to obtain K'
c) Compute eigenvalues λ and eigenvectors v of K'
d) Extract principal components as resultant feature vectors

2.2 Improved KPCA Dimensionality Reduction Algorithm (IKPCA)

Fall detection is fundamentally a classification problem. While traditional KPCA preserves original information effectively, it only considers feature space information content without fully incorporating class information, making effective feature vector acquisition uncertain. We therefore propose IKPCA, which maximizes classification information (intra-class compactness and inter-class separability) while maintaining KPCA' s dimensionality reduction capability and improving subsequent classification.

The 75 features extracted via time-domain analysis contain numerous invalid vectors that reduce reduction efficiency and accuracy. To mitigate this, IKPCA employs the I-RELIEF algorithm for feature selection before reduction, yielding fall feature vector set $\mathcal{B}'$ as shown in .

For each fall feature vector v_k in $\mathcal{B}'$, we compute intra-class compactness:

$$J_W(k) = \sum_{c=1}^{C} \frac{1}{n_c} \sum_{i=1}^{n_c} (x_{ik} - \mu_{ck})^2$$

where σ_k^2 is the variance of the k-th feature vector and C is the number of classes. Inter-class dispersion is:

$$J_B(k) = \sum_{c=1}^{C} (\mu_{ck} - \mu_k)^2$$

where n_c is the number of samples in class c, and x_{ik} is the k-th feature value of the i-th sample in class c. The class information measure is:

$$J(k) = \frac{J_W(k)}{J_B(k)}$$

Larger $J(k)$ indicates smaller class information and poorer separability. The set of feature vectors with smallest $J(k)$ values represents the most informative features for classification.

However, large class information alone doesn't guarantee improved classification accuracy. We therefore compute similarity measures between fall feature vectors and class vectors to select relevant features and eliminate insignificant ones. The similarity measure is:

$$\xi(v_i, v_j) = \frac{\text{cov}(v_i, v_j)}{\sqrt{\text{cov}(v_i, v_i)\text{cov}(v_j, v_j)}}$$

where v_i is a fall feature vector and v_j is a class vector. Non-zero similarity indicates correlation; values approaching zero indicate irrelevance. This eliminates minimally correlated features, reducing training complexity.

Algorithm 2: IKPCA Algorithm
Input: Initial fall feature vector set $\mathcal{X}$
Output: Final fall feature vector set $\mathcal{B}''$
a) Apply I-RELIEF to $\mathcal{X}$ to obtain $\mathcal{B}'$
b) Initialize $m \times m$ matrix (m = number of feature vectors in $\mathcal{B}'$)
c) Select Gaussian radial basis kernel parameters and compute kernel matrix K
d) Center K to obtain K' and compute its eigenvectors
e) Compute information measure $J(k)$ for each feature vector and sort ascending
f) Extract top n vectors $\mathcal{V}'$
g) Compute similarity measures $\xi(v_i, v_j)$ between $\mathcal{V}'$ and class vectors
h) Eliminate feature vectors with similarity approaching zero
i) Re-sort remaining vectors by similarity to obtain final set $\mathcal{B}''$ shown in

IKPCA' s computational complexity is $O(m^3)$ due to eigenvalue decomposition of an $m \times m$ matrix.

3.1 Experimental Scheme

To validate IKPCA' s effectiveness, we employ Support Vector Machines (SVM) as the classification algorithm, using classification performance on initial and reduced feature sets as evaluation criteria (initial features selected from UCI dataset). Three schemes are implemented:

Scheme 1: Initial feature vector set + SVM
Scheme 2: Initial feature vector set + KPCA + SVM
Scheme 3: Initial feature vector set + IKPCA + SVM

3.2 Algorithm Evaluation

Performance metrics derived from include:

a) Accuracy (Ac): Overall correct rate

$$Ac = \frac{TP + TN}{TP + FP + TN + FN} \times 100\%$$

b) Sensitivity (Se): Positive sample detection rate

$$Se = \frac{TP}{TP + FN} \times 100\%$$

c) Specificity (Sp): Negative sample detection rate

$$Sp = \frac{TN}{TN + FP} \times 100\%$$

Experimental results in and [Figure 1: see original paper] reveal that Scheme 1 (direct SVM on initial features) performs worst. Schemes 2 and 3, applying KPCA and IKPCA respectively before SVM classification, demonstrate that IKPCA significantly outperforms KPCA in dimensionality reduction effectiveness.

The results validate that our feature extraction and reduction approach improves fall detection rates by identifying appropriate, effective feature vectors. Compared to KPCA, IKPCA increases detection accuracy while incurring only 12.78% additional computational time—an acceptable trade-off for engineering applications.

4 Conclusion

Enhancing the rationality and effectiveness of fall process feature vectors is critical for fall detection. This paper extracts an initial feature vector set via time-domain analysis, then applies IKPCA for further reduction to eliminate invalid vectors, yielding a rational and effective final set. IKPCA maintains KPCA' s dimensionality reduction capability while delivering superior classification performance. Comparative experiments with datasets and SVM classification confirm that our approach produces higher-quality feature vector datasets.

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Note: Figure translations are in progress. See original paper for figures.