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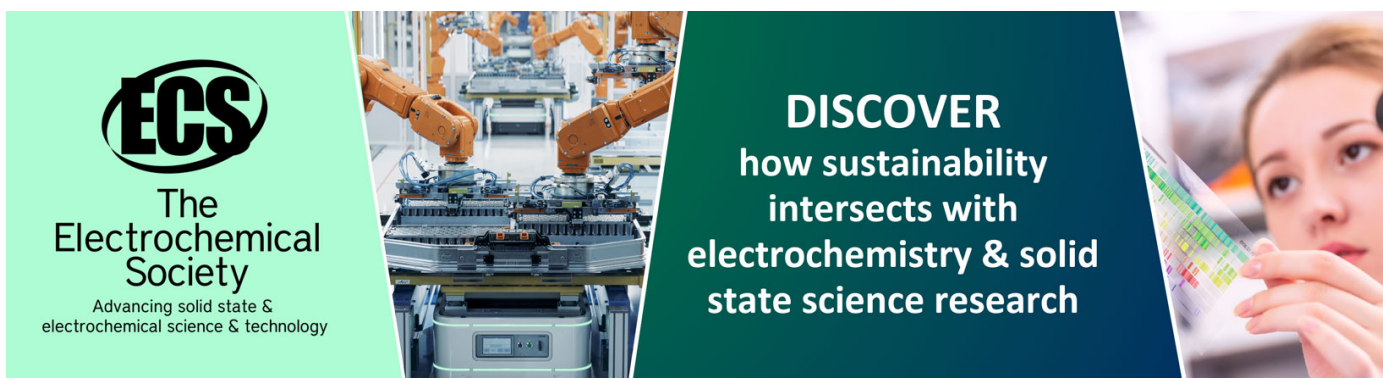
Valid Inertial Gait Data Recovery for Gait Recognition: A Multi-mode Adaptive Orthogonal Matching Pursuit

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Valid Inertial Gait Data Recovery for Gait Recognition: A Multi-mode Adaptive Orthogonal Matching Pursuit

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Abstract. Gait recognition based on inertial sensor data develops rapidly. Recently, more and more studies are based on the data collected in-the-wild, where the data quality is limited. Thus, the requirement for data preprocessing is higher. In this work, an adaptive preprocessing algorithm, MAOMP, is proposed to extract the effective components in the gait data. Different from traditional denoising methods, MAOMP recovers valid data from scratch using sinusoidal bases adaptively by projecting signals and bases into the Hilbert space. It can remove invalid data to smooth the signals but highlight the essential extremums at the same time. Finally, MAOMP is evaluated on four publicly available datasets of different grades and three different neural networks. The quantization of SNR shows the data recovered by MAOMP is at a higher level. Compared to the two commonly used preprocessing methods, the performance of MAOMP can be more pronounced as the quality of the datasets decreases. The improvements of the recognition performance are more apparent in the ConvLSTM network compared to the CNN with the data recovered by MAOMP.

Keywords. Orthogonal matching pursuit; gait recognition; deep learning; data preprocessing.

1. Introduction

Gait, one of the characteristics of human behavior [1]. Gait as a behavior feature to identify a person's identity has received extensive attention and research [2]. Furthermore, gait recognition technology has been widely used in information technology [3], smart home industry [4], health industry [5], sports industry [6], and other fields [7]. For the gait recognition based on sensor data, accelerometer and gyroscope sensors are usually used to collect data [8]. Before using the data collected by the inertial sensors for gait recognition, an appropriate preprocess for the data is necessary since raw gait data commonly contains various noises generated in multiple ways. Basically, they are generated by the friction between the sensors and the clothes during movements, the slight fluctuations of the device, and the device itself, etc.

In view of this, a new preprocessing method to improve inertial gait data, multi-mode adaptive orthogonal matching pursuit algorithm (MAOMP), is proposed and applied in this paper to eliminate noises and recover valid data. Specifically, the proposed MAOMP can adaptively process multi-mode gait time series data collected by accelerometers and gyroscopes. It is proven that its performance is better than that of the traditional wavelet denoising method and the weighted moving average method.



2. Materials and Methods

Proper preprocessing process is essential when the data quality is poor. In this section, we first illustrate the multi-mode data used in this paper. The MAOMP approach is then presented in detail. After that, two simple self-designed neural networks are introduced for the validation experiments.

2.1. Multi-mode Data

The data used in this paper for validation is acquired directly from various public available datasets, including the dataset collected in the wild and the dataset collected in an experimental setting. Specifically, multi-mode data refers to the data collected in different conditions of perceiving region, sensor, terrain, perceptive mode, walking speed, etc.

Four publicly available datasets are applied in this paper, which are Camargo's Biomechanics Dataset [9], Dataset #1 and #2 of whuGAIT Dataset [10], and OU-ISIR Dataset [11]. From the perspective of the challenge of classification tasks, datasets are graded into four levels as best, high, medium and common in this paper, where each level corresponds to an introduced dataset as below. As shown in table 1.

The quality of Camargo's Biomechanics Dataset is the best among the four afore-mentioned datasets. Each subject needs to walk at different speeds for different movements (walking on level ground, walking on a ramp, climbing stairs, etc.). At last, the data we use are collected on 22 subjects with 20,957 gait samples. Among all the seven datasets in the whuGAIT Dataset, which were collected in-the-wild, we select Dataset #1 and Dataset #2 as they are mainly tested in [10]. In particular, the former is collected on 118 subjects with 36,844 gait samples, while the latter is collected on 20 subjects with 49,275 gait samples. The quality grade of Dataset #2 is high while which of Dataset #1 is medium. OU-ISIR Dataset is a comprehensive gait dataset that was collected in a laboratory environment. Since the inertial gait time-series data presented for any single subject is short and was collected on 745 subjects in total, the data is sampled from the inertial sequence with a length of 128 time points and an interval of 50 to extend available data. In spite of this, the available data we ended up obtaining has limited samples with the number of 14,621 as well as large numbers of subjects, which means that the classification task is still challenging. For the above reasons, the dataset we use from OU-ISIR Dataset is graded into common quality.

Table 1. Details of the public datasets ^a.

Dataset	Number of subjects	Overlap in sampling	Samples for training	Samples for Test	Setting	Relative quality
Camargo	22	0	18,861	2,096	Laboratory	Best
whuGAIT #1	118	1 step	33,104	3,740	In-the-wild	High
whuGAIT #2	20	0	44,339	4,936	In-the-wild	Medium
OU-ISIR	745	0.78 step	13,212	1,409	Laboratory	Common

^a Note: There is no overlap between the training sample and test sample for all datasets.

2.2. MAOMP

The proposed MAOMP can recover the multi-mode gait time series data collected by accelerometer and gyroscope adaptively. The framework of the proposed algorithm is presented in figure 1.

Generally, a discrete signal can be represented by a linear combination of multiple sinusoidal components of various amplitudes, frequencies, and phases. Based on this, MAOMP can recovers each segmented data as a combination of sinusoidal bases that are in the frequency range which the valid data frequency mainly distributes. With the analysis of the low frequency generated from a normal gait through experiments, the range is set as 0.5 Hz to 10 Hz for all the channels, as can be seen in figure 2. Hence, the following redundant dictionary (D) was built to store the sinusoidal bases described above. Each of its columns represents a sinusoidal basis.

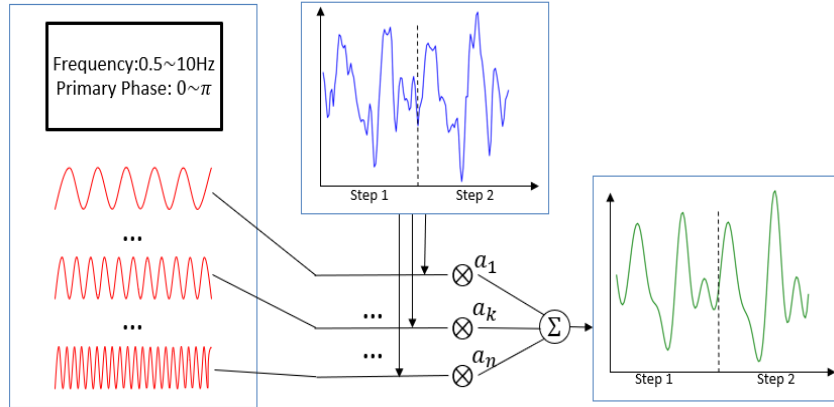


Figure 1. The framework of the MAOMP algorithm.

$$\begin{aligned}
 f_{ij} &= (\beta_i + \gamma_j)/2 \\
 D_{ijk} &= \alpha \sin(2\pi f_{ij}t + \phi_k) \\
 D &= [D_{111} D_{112} \cdots D_{ijk} \cdots D_{IJK}]^T
 \end{aligned} \tag{1}$$

where D_{ijk} is the sinusoidal basis whose frequency and initial phase are f_{ij} and ϕ_k respectively; f_{ij} is determined by both the β and γ parameters; the range of the β is range from 1 to 19, and the gap between β_i and β_{i+1} is 1; the range of γ is from 0 to 1; the gap between γ_j and γ_{j+1} is 1/30; the gap between ϕ_k and ϕ_{k+1} is $\pi/50$; t is an equally spaced vector of length 128 (the length of a single segmented data in our case); α is a constant taken as 1/2 in our case.

With the above redundant dictionary (D), we can reconstruct the segmented signals matrix(Y) as

$$Y \approx DX, \text{ satisfying } \|Y - DX\|_p \leq \epsilon \tag{2}$$

where X is the matching coefficient matrix and ϵ is the allowable error that is supposed to be constrained at a low level. Specifically, through the iterative greedy algorithm OMP [12], the sparse matching coefficients matrix was solved. OMP is a stepwise forward selection algorithm. In each iteration, the basis x in the dictionary (D) closest to the residual of the current sample is selected until the residual (error) r meets a specified condition.

2.3. Neural Network for Validation

ConvLSTM [13] has convolutional structures in both the input-to-state and state-to-state transitions, enabling it to extract more general spatial and temporal features at the same time. The LSTM network and the ConvLSTM network proposed for validation in this article are presented in table 2.

Table 2. Details of the proposed ConvLSTM network.

Layer Name	Units	Activation
ConvLSTM2D	32 (1 × 3)	Relu
Dropout & Flatten	/	/
Dense	128	Relu
Dense	n_output	softmax

3. Results

The designs and results of the validation tests are illustrated in this section, including performance tests and comparative tests. Through two comparative methods, the effect of MAOMP is analysed.

3.1. MAOMP Performance Testing

The processed inertial gait data are presented in figure 2 with frequency-domain spectrums. Obviously, MAOMP eliminates most of the invalid jitter in the raw data curve and recovers the valid data with a smooth curve. The frequency of the recovered valid gait data ranges from 0.5 to 10 Hz, strictly complying with the frequency range of the sinusoidal basis dictionary.

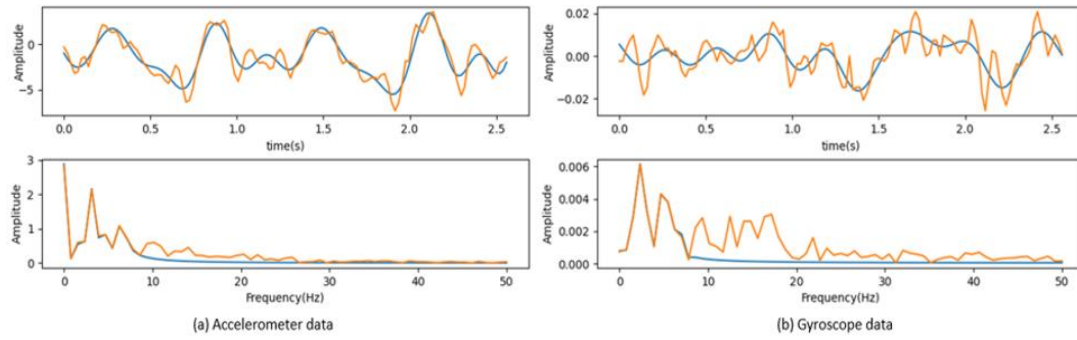


Figure 2. The data presented in the two subgraphs are accelerometer data and gyroscope data, respectively. Thereinto, the blue lines denote the valid gait data recovered by MAOMP, and the yellow lines denote the raw data.

Signal denoising using different techniques is plotted and compared in figure 3. It is easy to find that the signal preprocessed by WMA and DWT is very close to the raw signal, where the signal is mainly smoothed and de-noised to remove the burr. In contrast, the signals processed by MAOMP only contain the essential peaks and valleys, which are even highlighted in some local areas ulteriorly. Meanwhile, most of the meaningless fluctuations are removed directly. This process is actually the process of removing the jitter data, which is independent of the gait collected by the sensor.

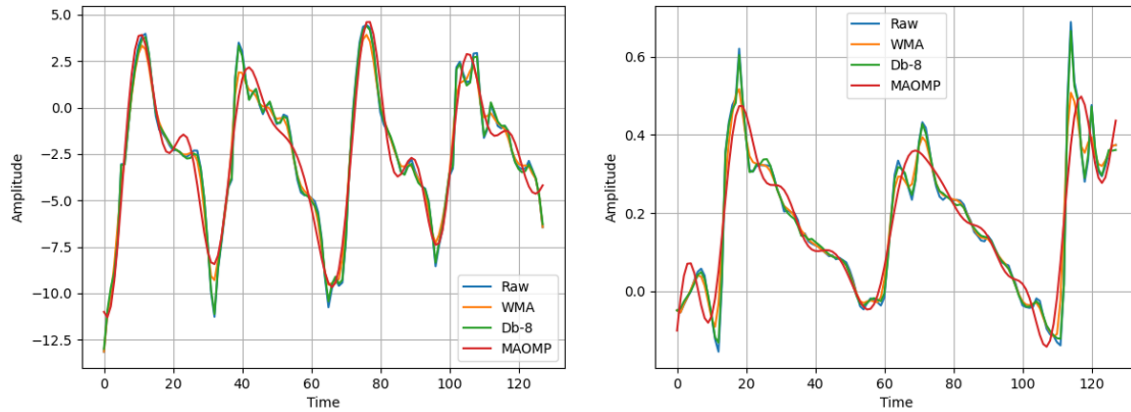


Figure 3. Comparison of signal preprocess using different techniques.

To further quantize the difference between raw data and the processed data, we analysed and calculated upon all the four datasets that are processed by the three methods mentioned above on the basis of the Signal Noise to Ratio (SNR). Initially, SNR mainly measures the ratio of the ideal signal to the noise in a signal. Since the ideal inertial gait signal has not been defined, we defined a variant of the SNR to quantize the differences as equation (3) and the results are shown in table 3.

$$mean_S_i = \frac{\sum_j^{128} S_{ij}}{128}$$

$$mean_R_i = \frac{\sum_j^{128} (R_{ij} - S_{ij})}{128}$$

$$SNR = 10 \times \log_{10} \left[\sum_{i=1}^N \sum_j^{128} \frac{(S_{ij} - mean_S_i)^2}{(R_{ij} - mean_R_i)^2} \right] \quad (3)$$

where subscripts i and j denote the i^{th} piece of the data and the j^{th} point of overall 128 points of single piece data, respectively; N represents the sample amounts of the datasets which are illustrated in table 1. Significantly, S and R denote the processed data and the raw data, respectively.

Table 3. Difference quantized by SNR upon the four datasets.

Datasets	SNR		
	WMA	DWT-Db8	MAOMP
Camargo (best)	-3.51	-2.91	-3.59
whuGAIT #2 (high)	-3.81	-2.93	-4.19
whuGAIT #1 (medium)	-3.82	-2.94	-4.10
OU-ISIR (common)	-3.34	-3.00	-3.29

3.2. Recognition Performance Testing

As shown in figure 4, there is a non-negligible improvement in the ConvLSTM network. Its validation accuracy always remains on top of accuracy based on the raw data, even though the accuracy of raw data is high.

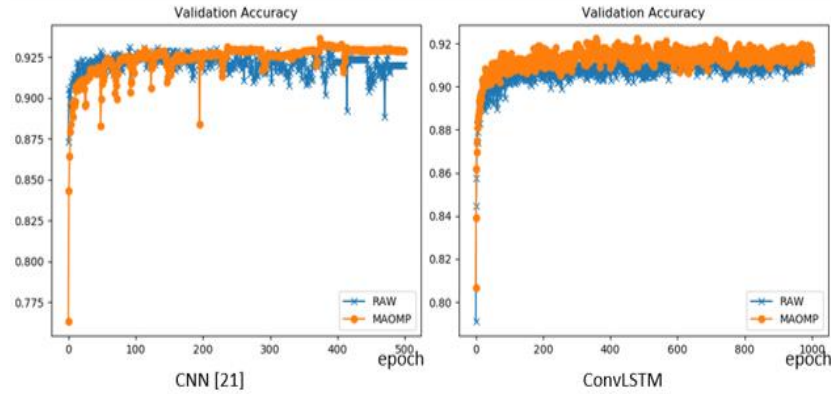


Figure 4. Validation Accuracy of gait recognition using the CNN and ConvLSTM upon whuGAIT Dataset #1 with the data processed by MAOMP.

3.3. Recognition Comparative Testing

In this section, the data processed by the three methods were fed into the ConvLSTM network, which has shown a better effect in Section 3.2 than the CNN. As can be seen from figure 5, the validation accuracy of the ConvLSTM network with the data recovered by MAOMP fed in is higher than that of the ConvLSTM network with the data denoised by WMA and DWT-Db8.

Ultiorly, the comparative experiments were conducted on all the datasets, and the validation accuracies are shown in table 4. Significant differences in processing effects can be seen on different quality datasets. In particular, upon the OU-ISIR Dataset, we can see the most apparent difference. Because of the common quality of the OU-ISIR Dataset, all the three networks did not achieve high accuracy. However, it is worth noting that the precision is improved more obviously after the MAOMP than the other methods. Based on exactly the same CNN network and adjusted hyper-parameter as presented in [10], the accuracy is further enhanced from state-of-the-art with the data recovered by MAOMP.

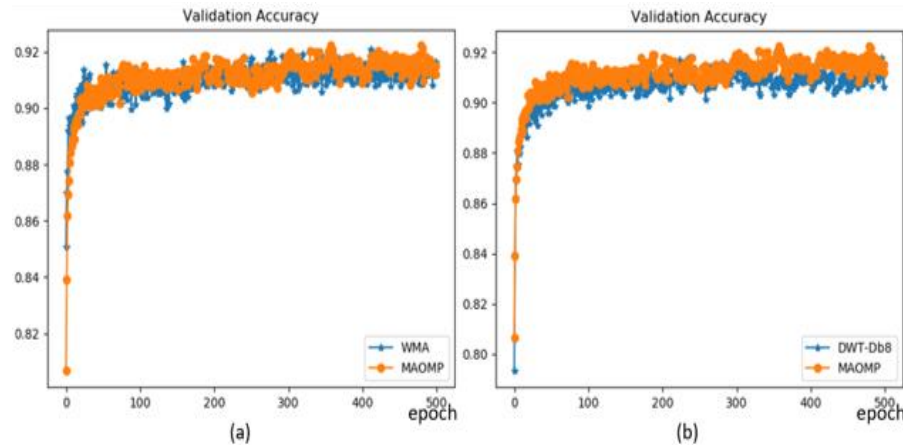


Figure 5. Validation accuracy of ConvLSTM network upon whuGAIT Dataset #1 using the three methods. Thereinto, (a) shows the difference between WMA and MAOMP, while (b) shows the difference between DWT-Db-8 and MAOMP.

Table 4. Results in the comparative test ^a.

Scheme		Raw	WMA	DWT-Db8	MAOMP
Camargo (best)	CONVLSTM	99.76%	99.67%	99.76%	99.76%
	CNN [10]	99.61%	99.18%	99.47%	99.71%
<i>whuGAIT</i> #2 (high)	CONVLSTM	96.78%	96.47%	96.70%	96.78%
	CNN [10]	97.02%	97.08%	97.20%	97.26%
<i>whuGAIT</i> #1 (medium)	CONVLSTM	91.74%	91.80%	91.84%	92.22%
	CNN [10]	92.89%	93.64%	93.64%	93.64%
OU-ISIR (common)	CONVLSTM	59.98%	60.11%	60.64%	61.82%
	CNN [10]	40.60%	38.54%	38.54%	40.95%

^a Note: The three results of gray background are directly the experimental results in [10], which are 97.02%, 92.89%, and 40.60%, respectively. Networks in all experiments were trained from scratch.

Comparing two networks performance upon different datasets, it is obvious that the data recovered by MAOMP can generally lead to higher precision and faster convergence in the various networks as well as different datasets. This phenomenon becomes more pronounced as the quality of the datasets decreases.

4. Conclusion

Gait recognition based on inertial sensor data has developed rapidly, with a large number of studies and applications appeared at present. Generally, the wavelet denoising method and the Weighted Moving Average method can smooth the signal, extract the effective signal and remove the invalid signal to a certain extent. However, when dealing with the poor-quality gait data generated in-the-wild, the traditional methods are of limited use because of the fixed weights, parameters, wavelet bases and so on. Therefore, we proposed the Multi-Mode Adaptive Orthogonal Matching Pursuit (MAOMP) method to specifically recover valid data. Since the frequency of the active components in the signal is within a certain range, MAOMP can use sinusoidal bases to extract the active components and combine them to recover effective signals. Ulteriorly, MAOMP has been proved to have a general and obvious effect on improving the accuracy of networks upon multi-mode data collected in various conditions. The proposed method can be used in future work to improve accuracy.

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