Research Square

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Motion Intent Recognition in Intelligent Lower Limb Prosthesis Using One-Dimensional Dual-Tree Complex Wavelet Transforms

Min Sheng
Anqing Normal University
Wanjun Wang
Anqing Normal University
Tingting Tong
Anqing Normal University
Yuanyuan Yang
Anqing Normal University
Huilin Chen
Anqing Normal University
Benyue Su (subenyue@sohu.com)
Tongling University https://orcid.org/0000-0003-1300-2083

Research

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Abstract

Background: Most traditional intent recognition methods are to recognizing the movement of lower limb prosthesis through statistical features, which are unstable in short-term signals. The another key problem with recognition of lower limb prosthesis motion intent is to explore the instantaneous change between the two diffffferent steady modes. Based on the above considerations, the one-dimensional dual-tree complex wavelet transform(1D-DTCWT) is introduced for motion intent recognition in intelligent prosthesis.

Methods: 1D-DTCWT adopts two-way complex wavelet transforms with a binary tree structure as functional data analysis (FDA) method that preserves the time-frequency local analysis capabilities of wavelet transforms while maintaining translation invariance and direction selection. Therefore, the 1D-DTCWT can amplify the instantaneous change information hidden in the data while retaining the continuity of the motion behavior, so as to better recognize the motion intention. Furthermore, the feature vector composed of low-frequency wavelet coeffiffifficients decomposed by 1D-DTCWT is classifified and recognized by support vector machine (SVM), which can effffectively classify and recognize the motion intent of the unilateral lower limb amputees.

Results: The data of the experiment comes from ten able-bodied subjects and one amputee subject to analyze 5 steady modes, 8 transitional modes, and 13 total motion modes adopting user-dependent and user-independent methods. The experimental results from the user-dependent methods show that the recognition rate for able-bodied subjects reached 98.91%, 98.92%, and 97.27% for the movement modes of steady modes, transitional modes, and total motion modes, respectively. The recognition rate of the amputee subject reached 100%, 91.16%, and 89.27%, respectively, for the three modes.

Conclusions: The method in this paper can effffectively solve the problem of short-term signal instability reflflected by traditional statistical feature recognition of motion intent and explore the instantaneous change information of transitional modes while retaining the continuity of the motion behavior.

Full Text

Due to technical limitations, full-text HTML conversion of this manuscript could not be completed. However, the latest manuscript can be downloaded and accessed as a PDF.

Figures

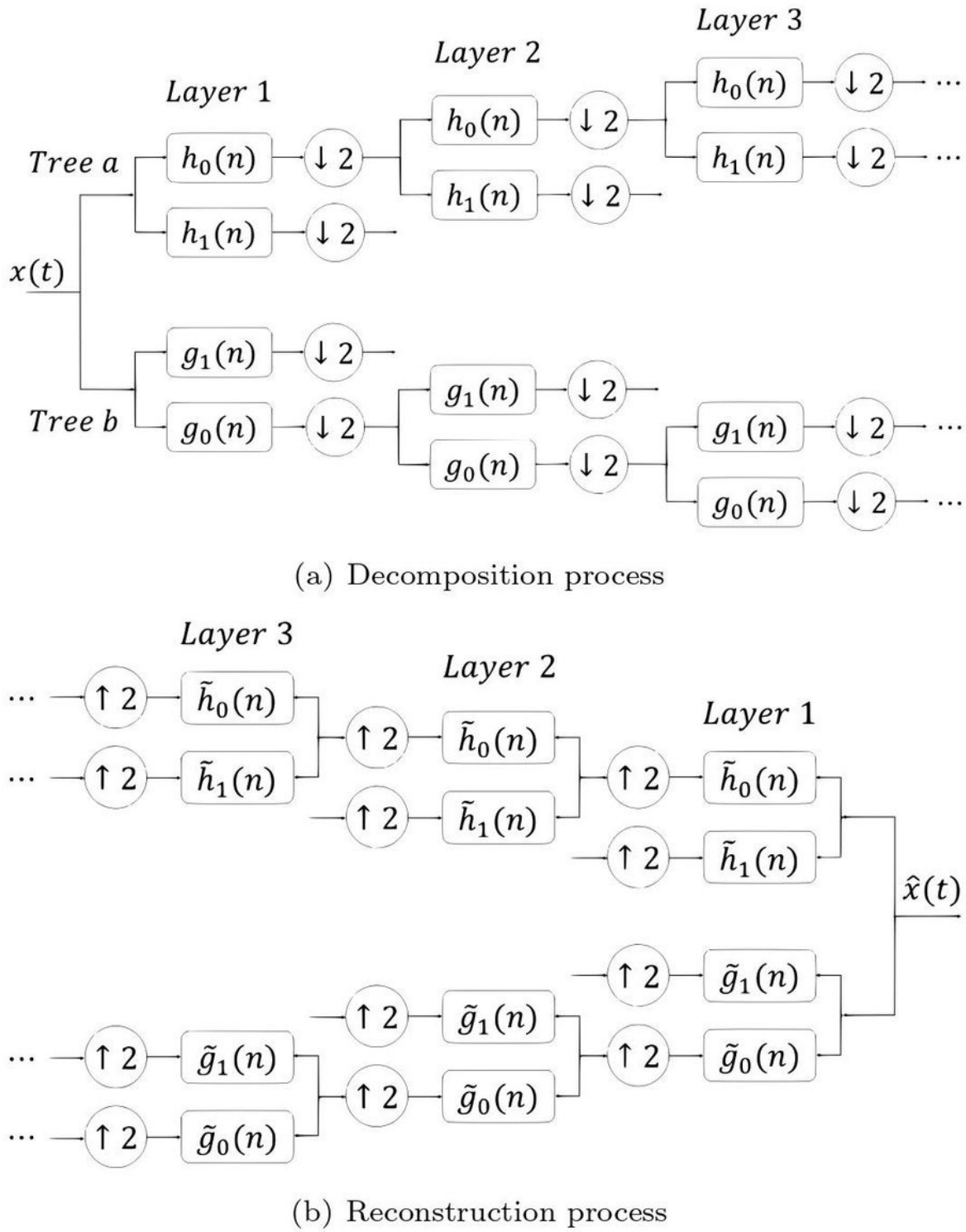
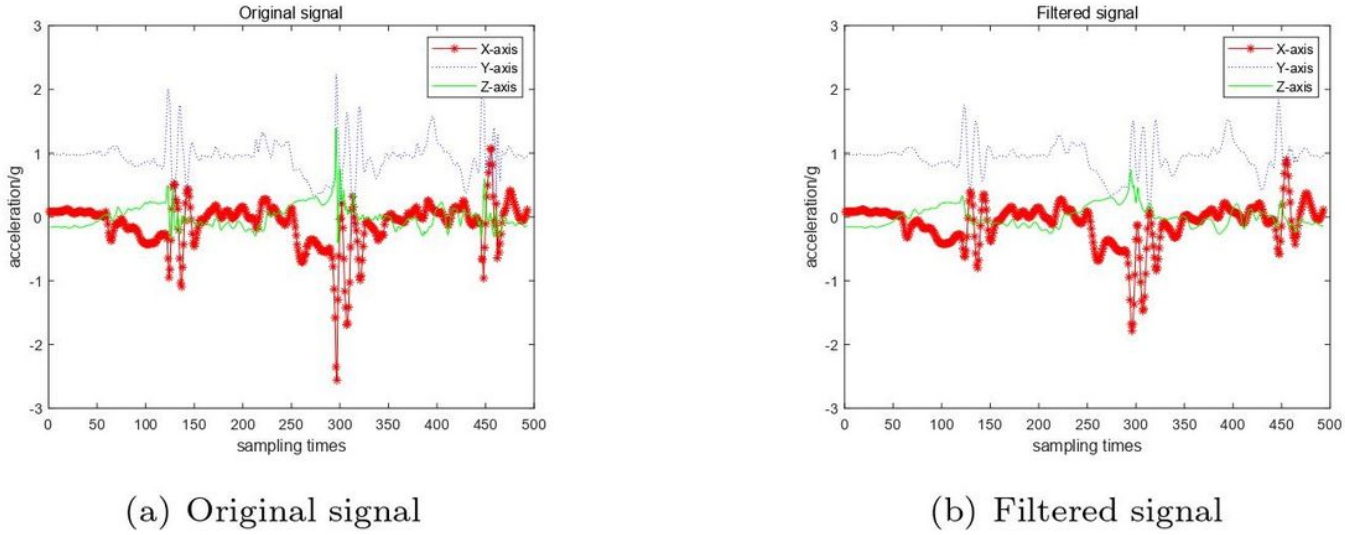


Figure 1

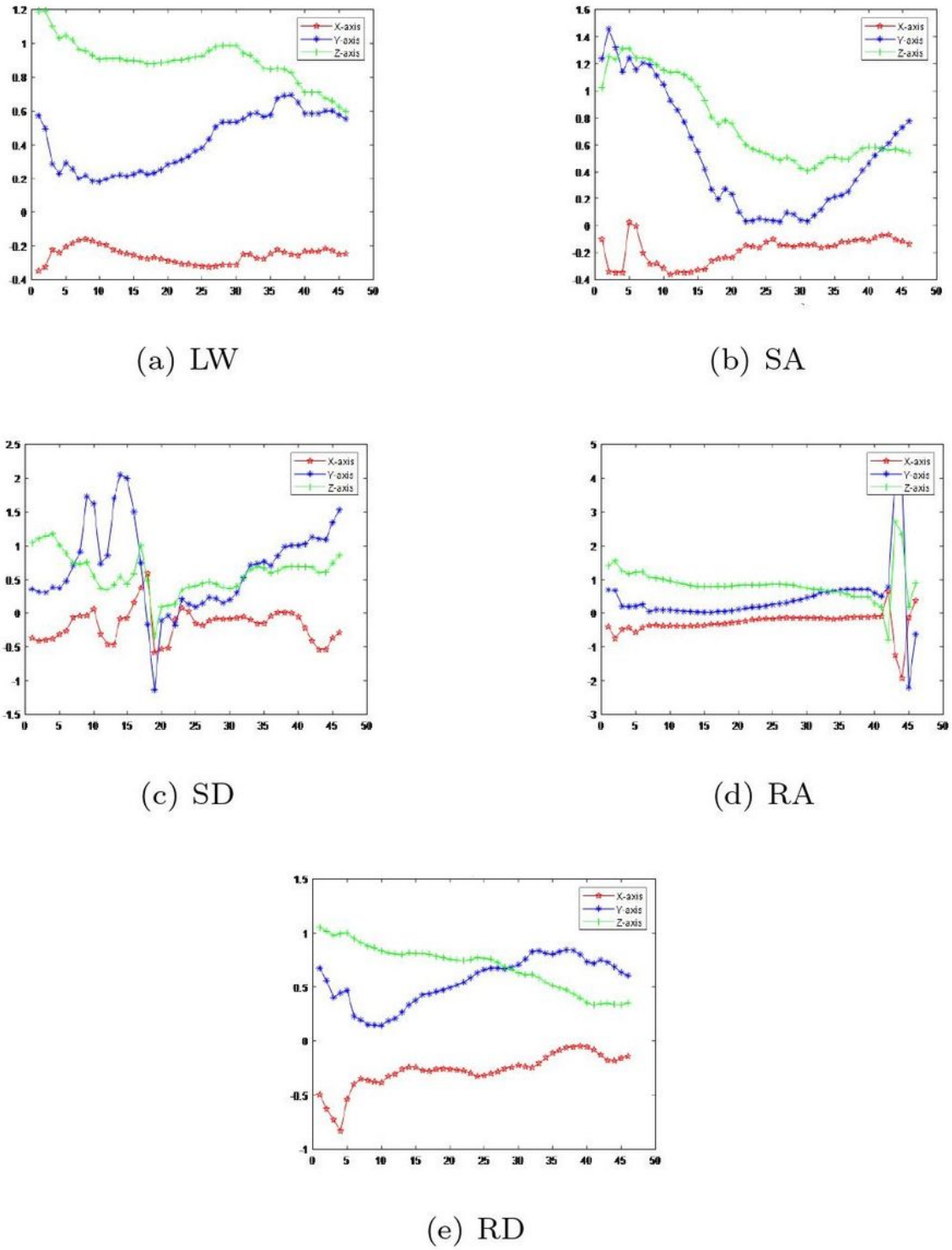
1D-DTCWT decomposition and reconstruction principles



(a) Original signal (b) Filtered signal

Figure 2

Accelerometer signals of LW-SA (from able-bodied subjects with sensor attached at the thigh)



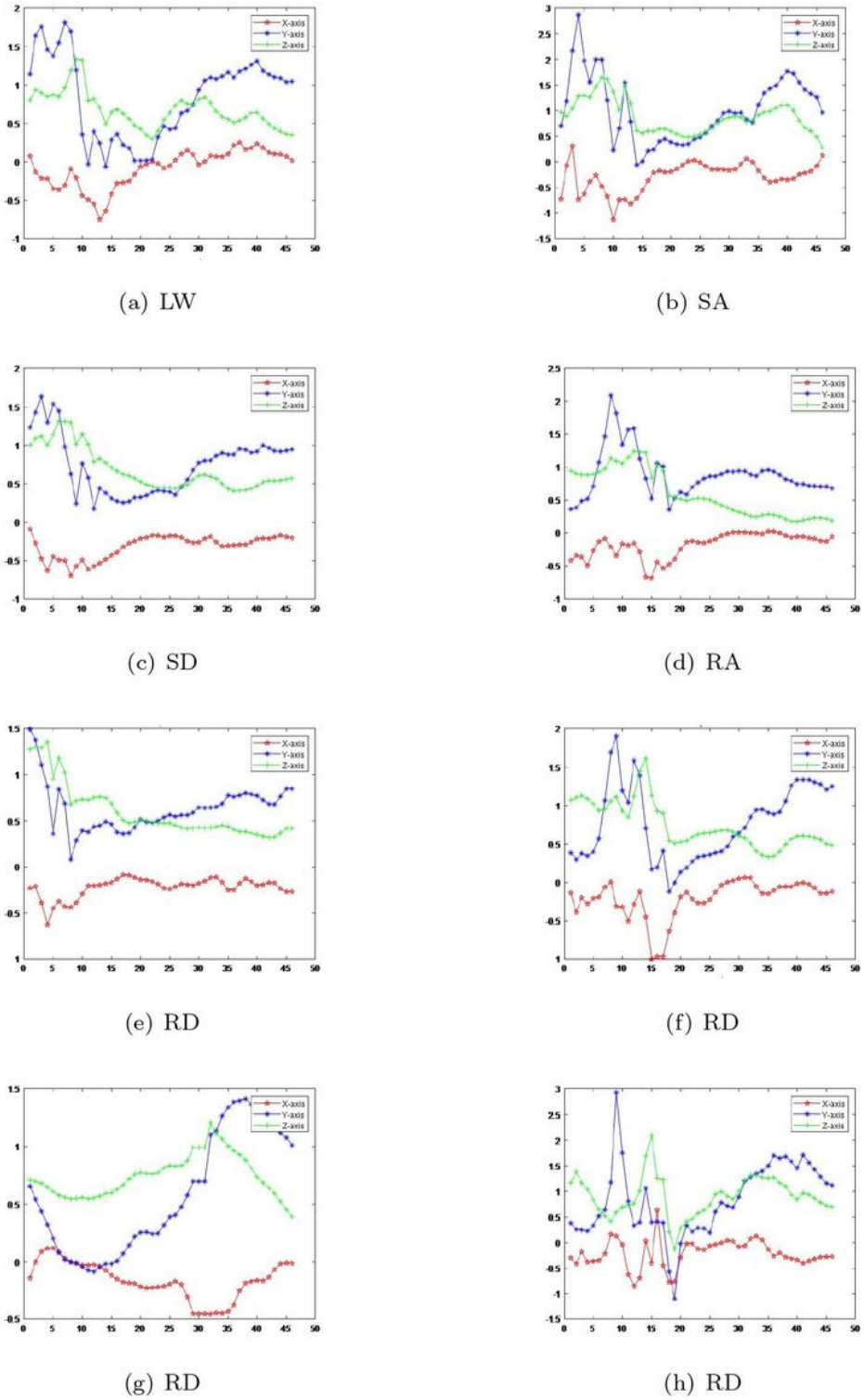
(a) LW (b) SA

(c) SD (d) RA

(e) RD

Figure 3

Accelerometer signals for the five steady modes when fitted by 1D-DTCWT (from able-bodied subjects with sensor attached at the thigh)



(a) LW (b) SA (c) SD (d) RA (e) RD (f) RD (g) RD (h) RD

Figure 4

Accelerometer signals of the eight transitional modes when fitted by 1D-DTCWT (from able-bodied subjects with sensor attached at the thigh)

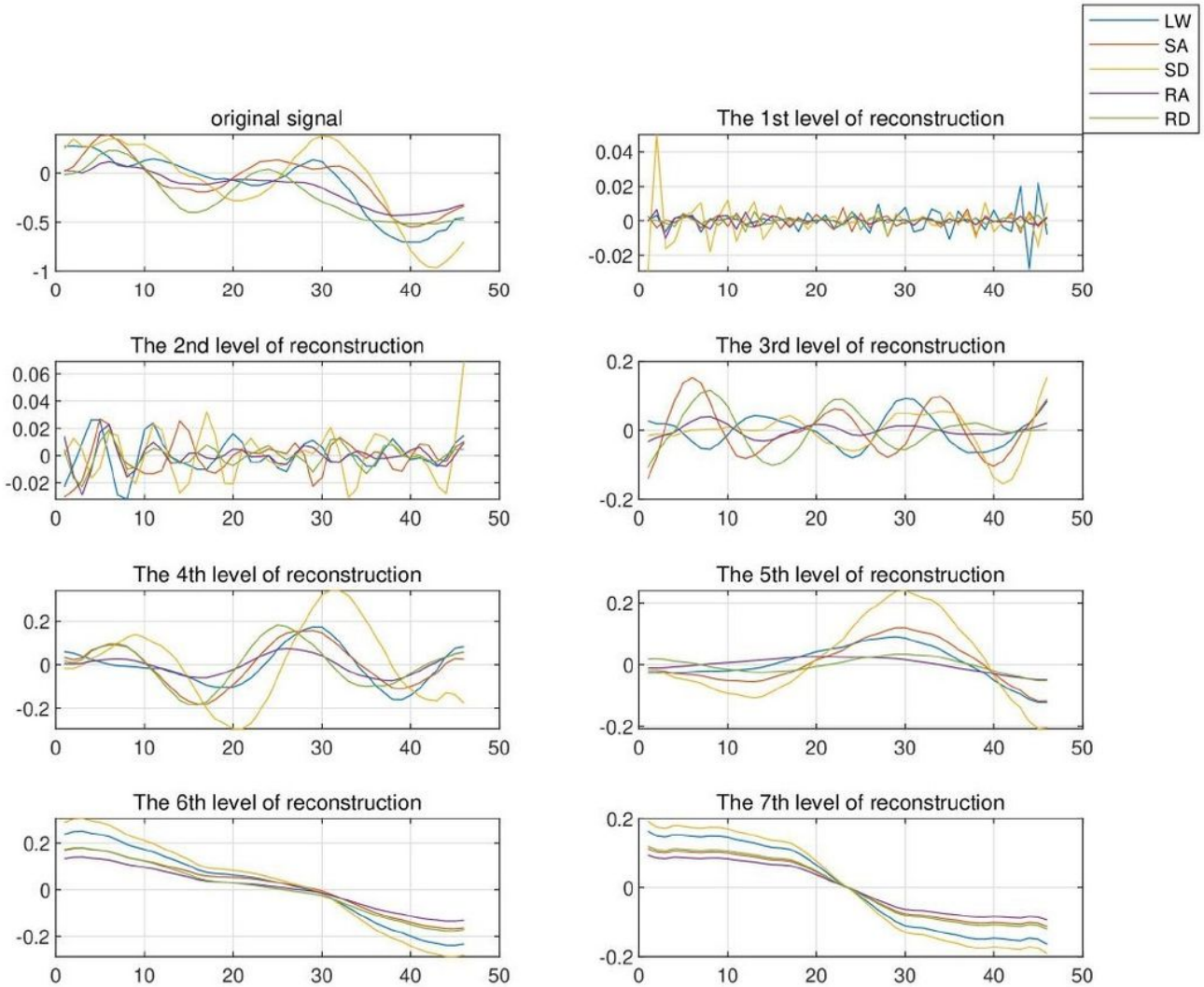


Figure 5

1D-DTCWT layer number reconstruction of steady modes (from able-bodied subjects with sensor attached at the thigh)

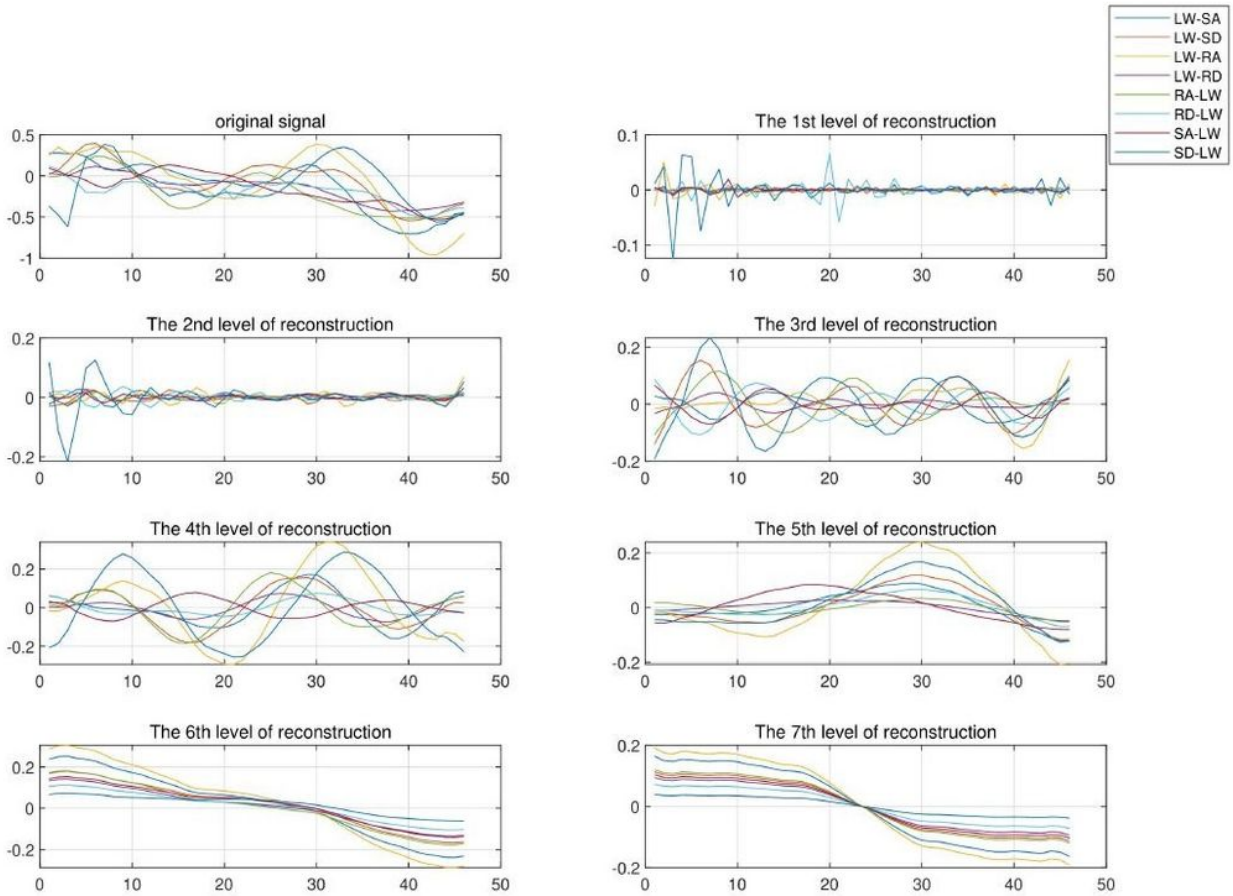


Figure 6

1D-DTCWT layer number reconstruction of transitional modes (from able-bodied subjects with sensor attached at the thigh)

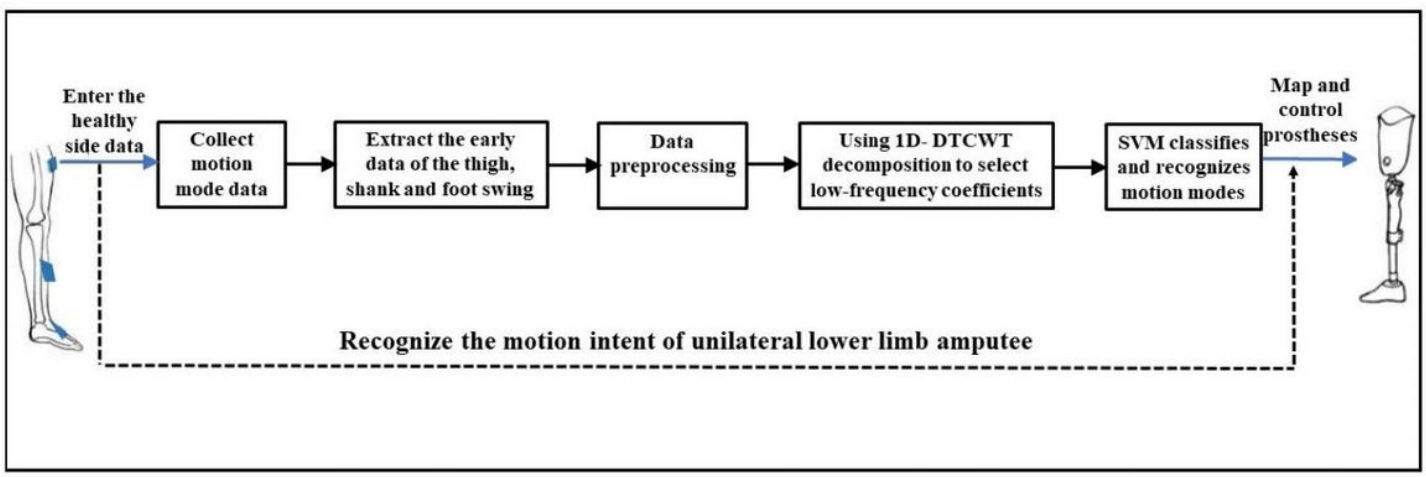
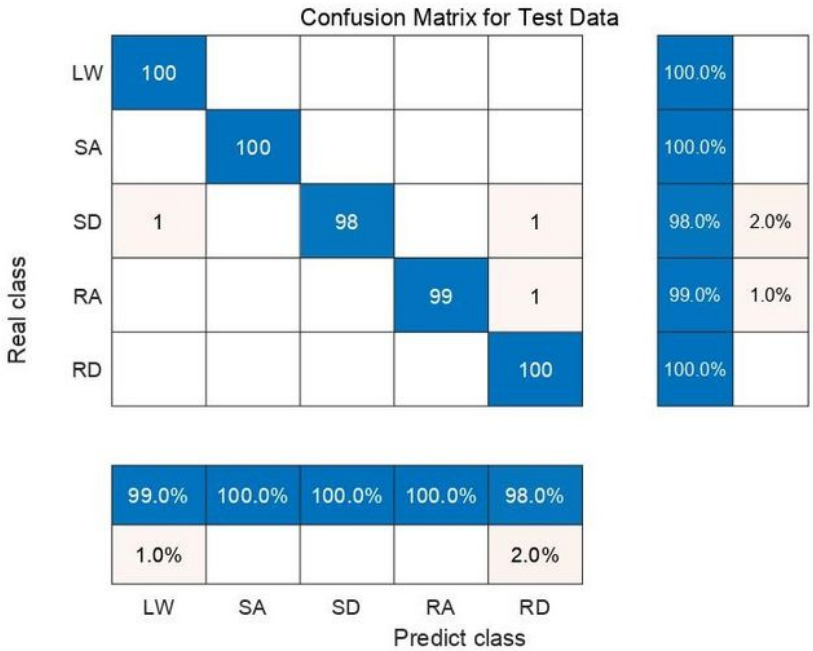
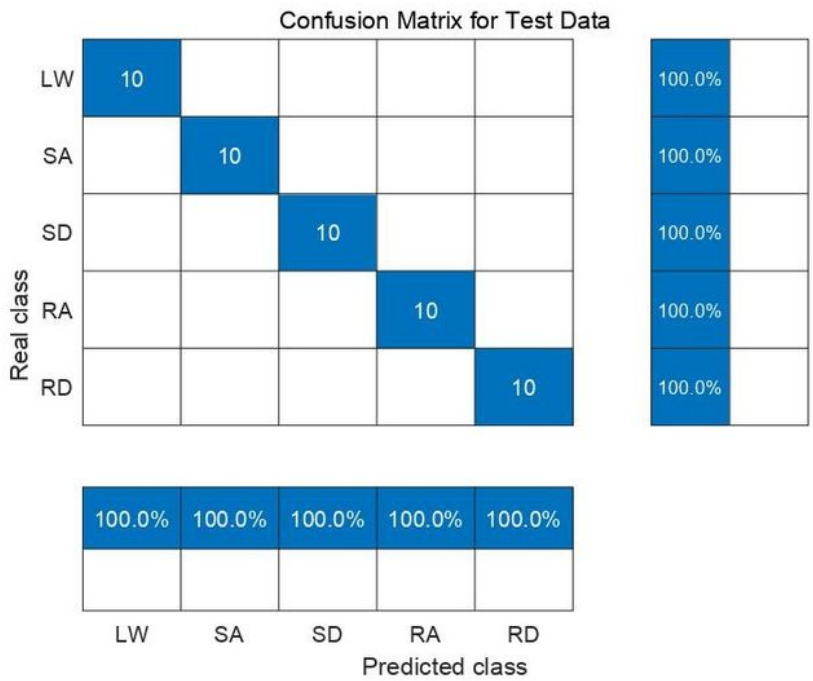


Figure 7

Motion intent recognition process



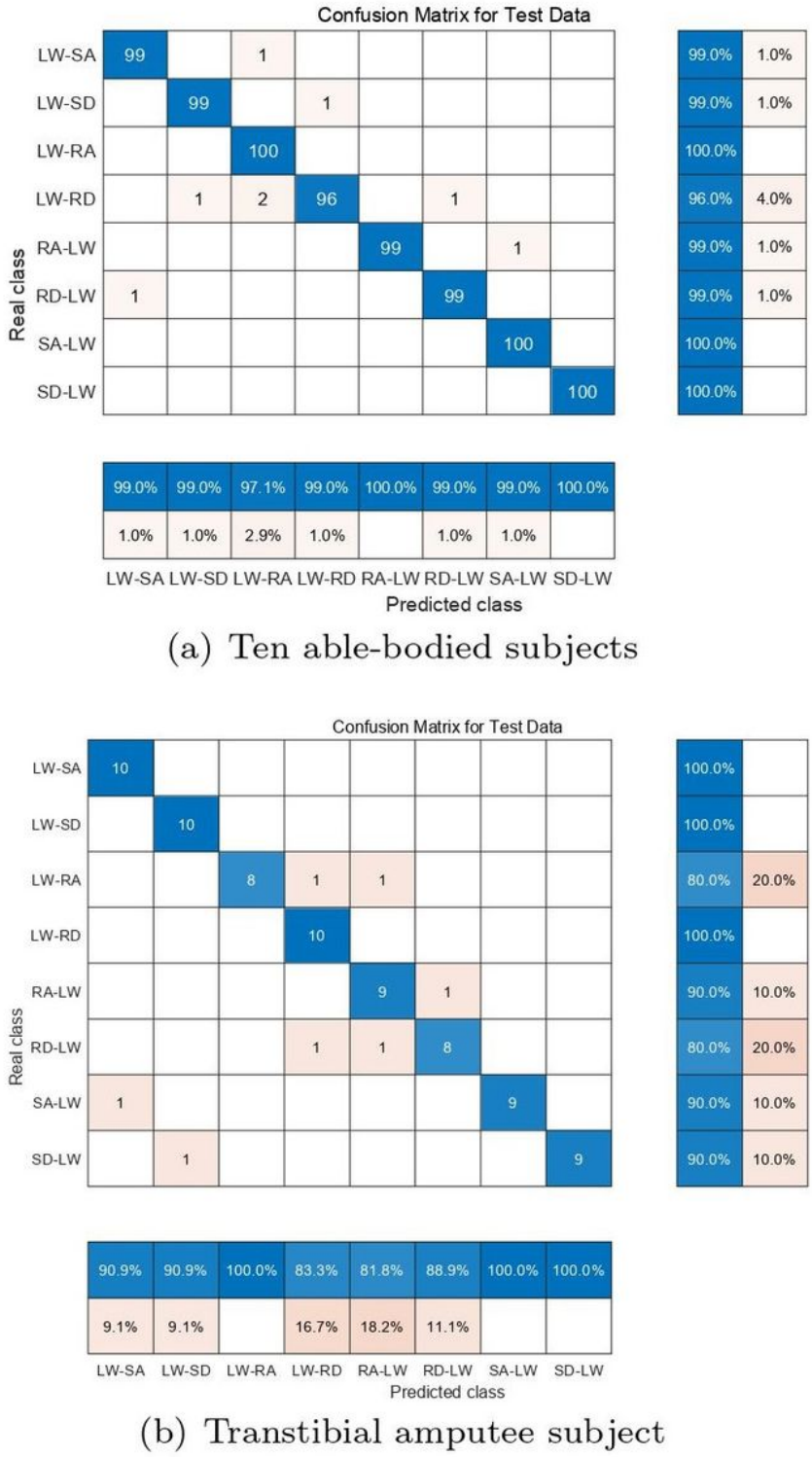
(a) ten able-bodied subjects



(b) Transtibial amputee subject

Figure 8

Steady mode confusion matrix with user-dependent classification

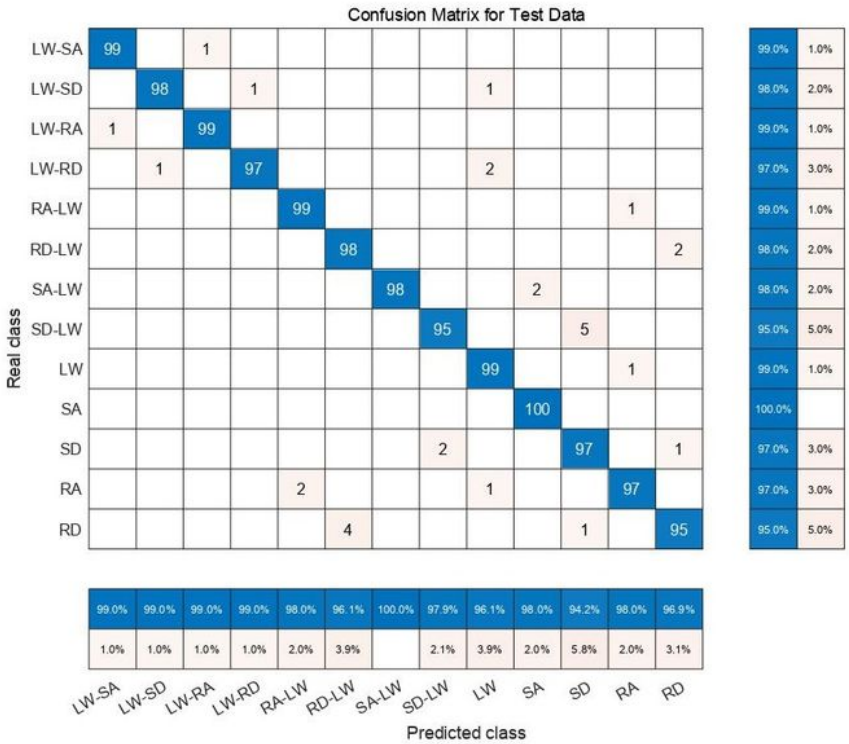


(a) Ten able-bodied subjects

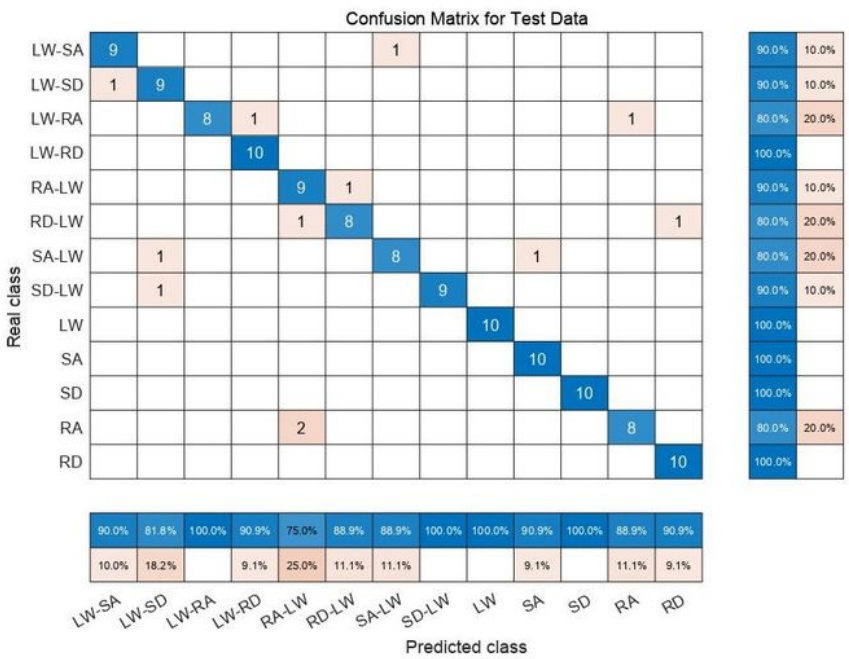
(b) Transtibial amputee subject

Figure 9

Transitional modes confusion matrix for user-dependent classification



(a) Ten able-bodied subjects



(b) Transtibial amputee subject

Figure 10

Sports modes confusion matrix for user-dependent classification

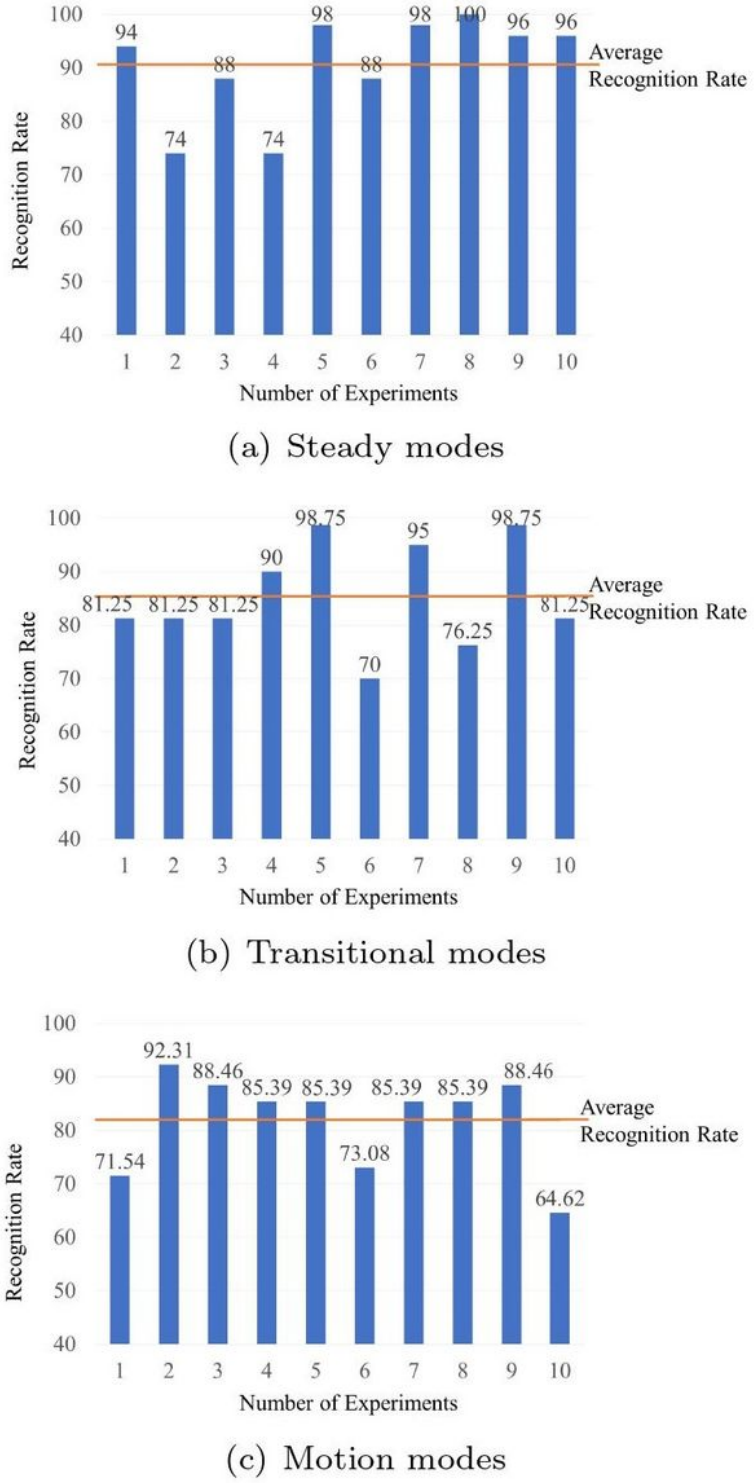


Figure 11

Tree diagram of able-bodied subjects' user-independent classification