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A survey of sensor fusion methods in wearable robotics

Domen Novak*, Robert Riener

Sensory–Motor Systems Lab, ETH Zurich, Tannenstrasse 1, CH-8092 Zurich, Switzerland

HIGHLIGHTS

- Overview of sensor fusion in wearable robots like prostheses and exoskeletons.
- Main sensors: electromyography, electroencephalography, and mechanical sensors.
- Emphasizes multimodality, adaptation and switching between sensor fusion schemes.
- Online evaluation of sensor fusion methods is crucial.

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ABSTRACT

Modern wearable robots are not yet intelligent enough to fully satisfy the demands of end-users, as they lack the sensor fusion algorithms needed to provide optimal assistance and react quickly to perturbations or changes in user intentions. Sensor fusion applications such as intention detection have been emphasized as a major challenge for both robotic orthoses and prostheses. In order to better examine the strengths and shortcomings of the field, this paper presents a review of existing sensor fusion methods for wearable robots, both stationary ones such as rehabilitation exoskeletons and portable ones such as active prostheses and full-body exoskeletons. Fusion methods are first presented as applied to individual sensing modalities (primarily electromyography, electroencephalography and mechanical sensors), and then four approaches to combining multiple modalities are presented. The strengths and weaknesses of the different methods are compared, and recommendations are made for future sensor fusion research.

1. Introduction

Wearable robots have developed rapidly over the last decades and have demonstrated their ability to assist humans in a variety of military, medical, and industrial applications. Perhaps the most iconic examples of such wearable robots are full-body exoskeletons such as the Hybrid Assistive Limb (HAL) [1], but smaller powered orthoses are no less important. Furthermore, powered prosthetic arms [2] and legs [3] also represent a type of wearable robot.

Existing wearable robots face numerous challenges with regard to both hardware and software. One major challenge is that the robot usually lacks the capability to adequately recognize the actions and intentions of the human wearer. Consequently, it cannot properly assist the wearer, a drawback that has been emphasized both in exoskeletons [4] and prosthetics [5]. In an effort to overcome these challenges, engineers have used numerous sensors and inference methods to obtain information about the wearer's intentions.

In many cases, the sensors used are those already built into the wearable robot, such as joint angle sensors. More advanced approaches incorporate electrophysiological measurements such as electromyography (EMG) or electroencephalography (EEG), or alternatively mechanical sensors placed on a part of the body that is not covered by the wearable robot. Recently, there has been a push to combine multimodal information, combining different sensor types to obtain a more complete picture of the user [6–9]. Multimodal information, however, also requires new sensor fusion algorithms.

This paper presents a review of sensor fusion algorithms for wearable robots, both robotic orthoses (e.g. exoskeletons) and prostheses. It is aimed primarily at engineers who need to convert raw sensor data to information about the wearer's actions and motor intentions and is divided into two larger sections. The first covers unimodal systems, where multiple signals are obtained from a single type of sensor (though multiple sensors of the same type are generally used). Section 2 covers multimodal systems, where it is necessary to combine signals from different types of sensors altogether. While there have not been detailed reviews

* Corresponding author. Tel.: +41 774470158.
E-mail address: domen.novak@hest.ethz.ch (D. Novak).

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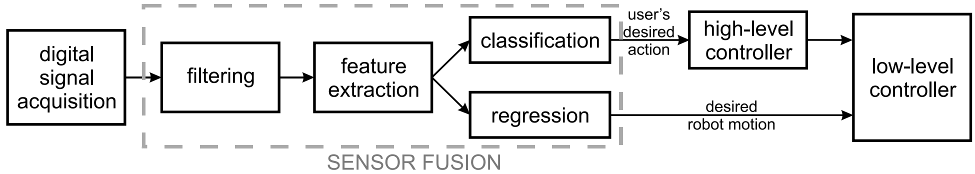

Fig. 1. Overall structure of the robot's decision-making process.

of sensor fusion for multimodal systems, several reviews do exist for unimodal systems [10,11]. We attempt to go beyond these reviews by providing an overview of algorithms for different signals and different devices together, emphasizing areas where, e.g., sensor fusion for prosthetics may be better developed than for exoskeletons or where, e.g., sensor fusion for EEG could learn a lesson from EMG systems.

As the state of the art is extensive, we narrowed the focus in a few ways.

- Classic control strategies such as impedance control are only mentioned briefly, as they have been very well-reviewed in other publications and are generally not considered sensor fusion.
- Not every example is referenced for every sensor fusion algorithm; if numerous systems use essentially the same algorithms, only the most informative examples are given.
- We only review sensor fusion approaches that are used with a wearable robot or in similar conditions. For example, systems that use EEG to control a robot arm are included; systems that control a cursor on a screen are not.
- Sensor fusion approaches must be used for real-time robot control or clearly suitable for real-time use.

We begin the paper by introducing some general terms related to sensor fusion in Section 2. Section 3 presents unimodal sensor fusion, where a single modality is used in classification or regression. Section 4 then presents multimodal sensor fusion, where two or more modalities are used. Section 5 briefly discusses sensor fusion performance evaluation, regardless of modality or sensor fusion algorithm. Finally, Section 6 concludes the paper with a summary and general discussion of the state of the art in wearable robotics.

2. General terms

The general process of robotic decision making is shown in Fig. 1. The first step of the process, signal acquisition, will not be covered in this paper.

Filtering is the first, preprocessing stage of sensor fusion. It almost always includes **bandpass filtering**, which removes all components of the raw digital signal except those in a defined pass band (e.g. 20–500 Hz for EMG). This removes low-frequency mechanical artefacts and high-frequency aliasing effects. Other possible types of filtering include notch filtering to remove electrical noise at 50 or 60 Hz or spatial filtering to remove unwanted signal components in the same frequency band as the useful signal [12].

Feature extraction is the process of extracting useful information ('features') from filtered signals. This can be as simple as rectification, but more complex features such as spectral power distribution are also common. Notably, features do not need to have the same sampling frequency as the raw signals. Instead, feature extraction commonly includes **segmentation**, which divides the raw signals into **windows**—intervals of a defined length. Features are extracted over the entire window and are output at the end of the window. A window can optionally overlap with the previous window, which allows more frequent commands to the robot and fewer sudden changes in sensor fusion output. An example of feature extraction from windows is shown in Fig. 2.

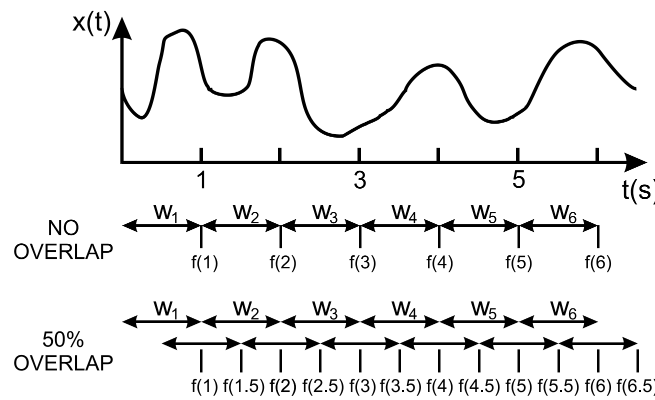

Fig. 2. Windowing and feature extraction for a signal $x(t)$ with 1-s windows. w represent windows while $f(T)$ represent features extracted at time T from the corresponding window. In the first example, windows do not overlap; in the second example, each window overlaps the preceding one by 50%.

Classification and regression are alternatives to each other, and a wearable robot generally utilizes one or the other. Multiple features are used as inputs simultaneously. A good introduction to both approaches is available from Bishop [13], but in wearable robotics:

- **Classification** assigns a discrete label to extracted features (e.g. "hand closing", "leg lifting"). This discrete label generally represents the action that the user wants to perform, and a high-level robot controller is necessary to decide how to react to this desired action. The high-level controller outputs the velocity/torque the robot should apply, and a low-level controller ensures that this velocity/torque is applied.
- **Regression** converts features to continuous values (e.g. joint torques). These values represent either the velocity/torque the user is trying to apply or directly the velocity/torque the robot should apply. Therefore, only low-level rather than high-level robot control is required.

In prosthetics, classification is sometimes referred to as "pattern recognition based control" while regression is sometimes referred to as "proportional control" or "continuous decoding". For simplicity's sake, we refer to both by their general, field-independent names.

Most classifiers are based on supervised machine learning: they learn classification rules from a set of previously recorded and labelled training data [13]. The accuracy of such classifiers is then defined as the percentage of correct class assignments. Regression is also often based on supervised machine learning, but can also utilize manually defined regression rules. As continuous output values allow smoother control, the sampling frequency of features for regression is generally higher than for classification and can be as high as that of the raw signals.

Robot control takes the results of classification or regression and converts them into the command given to the wearable robot's actuators. Though it will not be described in detail, readers should keep in mind that, as mentioned above, classification requires more complex (high-level) robot control algorithms than regression.