Gesture Recognition Techniques for the LMC

We undertook a Systematic Literature Review (SLR) [1] to determine the algorithms used for LMC-based gesture recognition. We ran the search query "*[Full Text: "leap motion"] AND [Full Text: "gesture recognition"]*" on The ACM Guide to Computing Literature, the option covering both the ACM Digital Library of references and its associated venues[1]. The query was performed on September 20th, 2020 and resulted in 390 publications. After removing six duplicates and excluding 341 irrelevant references (266 based on their title, abstract, and introduction, and 75 based on their full-text), we identified 43 references with a LMC gesture recognizer (Table 1).

Type	Algorithm	References
Opportunistic	Hard-Coded Thresholds	[2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12]
	Leap Gestures	[3, 13, 14, 15, 16, 6, 7, 8, 10, 17]
	GameWAVE Software	[15]
Nearest Neighbor	K-Nearest Neighbors	[18, 19, 20, 14, 21, 22, 23, 24, 25]
Support Vector Machines	Support Vector Machine	[26, 21, 27, 28, 29, 30, 31, 32]
Neural Networks	Multilayer Perceptron	[33, 34]
	Deep Feedforward Neural Network	[35]
	Feedforward Neural Network	[36]
	Gated Recurring Units	[25]
	Neural Network	[27]
	Radial Basis Function Network	[37]
Hidden Markov Models	Hidden Markov Model	[38, 39, 40, 41]
	Coupled Hidden Markov Model	[42]
Ensemble Learning	Random Forest	[30, 35]
	Bagging Trees	[27]
	Gradient Tree Boosting	[28]
Other AI/ML Techniques	Decision Tree	[21, 12]
	Decision Table	[43]
	Linear Discriminant Analysis	[27]
	Fuzzy Integral	[43]
	Multinomial Logistic Regression	[28]
	Naive Bayes	[44]

Table 1: Summary of the gesture recognition algorithms identified in the SLR.

The vast majority of analyzed publications ($\frac{16}{43}$=37%) implement gestural support in an opportunistic manner, *i.e.*, by relying on the few system-defined gestures natively supported by the LMC or by recognizing gestures based on hard-coded thresholds (*e.g.*, [2, 5, 12]). While this opportunistic approach may be appropriate in some cases (*e.g.*, for quick prototyping [45] or very simple UIs), it often forces developers to make significant compromises that could be avoided with more advanced recognition techniques. For instance, Liang *et al.* [15] designed a storytelling system in which children interact with hand gestures, but these gestures are hard-coded and cannot be modified easily to better fit the motor abilities and preferences of each child. Zocco *et al.* [17] showed that an LMC-based system could be more efficient than the traditional trackpad-keyboard combination to interact with a Command and Control system. However, as they were limited to the system-defined gestures, they did not study whether more suitable gestures could result in better usability, such as those obtained with user-defined gestures [46].

Found in nine references ($\frac{9}{43}$=21%), K-Nearest Neighbors (KNN) classifiers [47] are also a popular choice for gesture recognition. These algorithms are a simple yet powerful alternative to the opportunistic approach as they are easy to implement and to train while being reasonably fast and accurate. Some are presented as all-purpose recognizers [18, 24] while others target more specific applications such as handwritten numerals recognition [19] and Sign Language recognition, which remains a key topic for any language: American [26, 35, 33, 42], Greek [32], and Thai [25].

[1] See `https://dl.acm.org`

The remainder of the papers use more advanced ML techniques such as Neural Networks (NNs) from Deep Learning, Support Vector Machines (SVMs), Hidden Markov Models (HMMs), or Ensemble Learning. These techniques are used in all kinds of applications. For instance, Simos and Nikolaos [32] use an SVM to classify the 24 letters of the Greek Sign Language alphabet with high accuracy, and Kumar *et al.* [38] train an HMM to recognize words from single-stroke Latin sentences drawn in mid-air.

Finally, some papers combine algorithms and/or sensors. Daniels *et al.* [14] combine the LMC native gestures with the $1 recognizer [48] to recognize a larger set of gestures for manipulating protein structures. Jiang *et al.* [27] combine an LMC with myography data, Marin *et al.* augment the LMC with a Microsoft Kinect [49] or a depth sensor [30] to increase accuracy.

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