Identification Through Interaction

NO AUTHORS

1 Introduction

[ESS: *you need to include matthias as an author, even if he's not last author, and we need to run the paper by him before submitting*] Why do we care? Why is it hard? Why can we do it?

Recognizing individuals is critical to forming strong relationships. Person identification is primarily accomplished with face or voice recognition, but these modalities are sensitive to environmental conditions that make them unreliable in many industry applications. Some applications, like Amazon's Smart Speaker, can get around this with hardware design and big-data enabled machine learning, but this is not possible for many organizations and may not be a desired feature from the user's perspective. Robust voice and face recognition allow a user to be tracked across multiple contexts, but identification through interaction isn't likely to be translatable in the same way, giving the user the benefits of personalized interaction without restricting their right to privacy. [JSS: *Putting this argument here makes sense given the context, but it seems weird to do it before the topic of the paper is introduced. Should I just make the footnote longer?*]

Other identification schemes, like gait detection, require the user's full body to be recorded for multiple striding frames [3][2]. It's unreasonable to expect every piece of interactive technology to implement robust person identification systems with these restrictions in mind. However, most embodied piece of interactive technology can benefit from remembering previous interactions with individual users, and so a more reliable, scalable person recognition scheme is needed.

This paper attempts to implement the groundwork for an alternate identification system that can be used with any socially interactive device [ESS: *I'd suggest you scope this a little bit more – maybe socially interactive?*][JSS: *Added 'groundwork for' and 'socially'*] by using the interaction itself to better recognize individuals. Prior work in open-set recognition has only used static features of the user, but a key feature of an interaction is that it includes behaviors that are embedded in time. In this work we present a novel method for doing open-set recognition on time-series data, and discuss how this work can be extended to address the problem of recognition through interaction. We evaluate our system on a preexisting dataset and discuss how it could be extended in a case where the agent is able to take action.

[JSS: *Alternate for simple SVM implementation*] Prior work in open-set recognition...are embedded in time. In this work we present a novel method for user recognition on time-series data with a support vector machine, and discuss how...recognition through interaction and open-set recognition. We evaluate our system...is able to take action.

[ESS: *note that this specifies what sub-part of the problem you're addressing; if you want to address a different sub-part, you'll need to phrase it differently*]

2 Background Related Work

TODO: Don't write a book report. Only bring things up as they relate to our formalization of the problem. (1) work on multi-class SVM and where we fit in. (2) How multi-class SVM extends to open-set recognition and applying our strategy to the formalization of that extension.

2.1 Problem Formalization

We aim to identify a set of users $u_n \subseteq U$, where the number of users in the set, and so n, are unknown. Each user exhibits interactive behaviors that are measurable as k time-series signals.

$$b^k \subseteq B_n \tag{1}$$

[JSS: *Try to show more obviously that these are time series signals.*]

$$[b_0^k ... b_f^k] \in b^k \tag{2}$$

Where b^k is the time-series interactive signal, and b_t^k indicates whether the interactive behavior is present at time-step t. We need to take the time-series interactive behavior and convert it into an SVM classifiable signal, so b^k is converted into a discrete set of i features in d^k.

$$[d_0^k ... d_i^k] \in d^k \tag{3}$$

Where each entry in d^k is an extracted feature that describes an aspect of the time-series signal b^k. We can then feed the extracted features into n one-against-all Support Vector Machine which finds the hyperplane that separates the target class from the rest of the data by finding w and b in the following equation. [1]

$$D(x) = w^t x + b \tag{4}$$

Where w is a $k * i$ (the number of time-series signals times the number of features extracted from each signal) dimensional vector and b is a scalar. These values are found by training on a labelled subset of the data.

3 Technical Approach / Methodology / Theoretical Framework

[JSS: *shorthand brainstorming, needs editing*]

Signal making up B_n are handled without taking the meaning of the signal into account. We want to build a system that generalizes across interaction types. Each signal in B_n occurs over a time period. In a given segment of the interaction each signal will be present or absent at each timestep. Using only this information we have can produce a range of potentially useful features.

1. Active Ratio - For what percentage of the snippet was the signal active.
2. Total oscillations - How many times did the signal toggle from on to off (normalized by snippet length).
3. NEED a measure that connects different b^ks and/or catches coordinated transitions between signals. Encodable by an SVM? You could do a transition matrix (e.g. b^0 turned off within *epsilon* seconds of b^1 turning on x times in this snippet). But that's a k^2 on its own.

The above potential signals can be compared to the average value
[JSS: *SLAUNCHWISE*]
[JSS: *Frequency domain - connecting different signals. Spectral analysis.*]
[JSS: *Covariance matrix - Eigenvectors / Eigenvalues and how they relate different variables to each other.*] [JSS: *ROC curves for each combinations*]

3.1 AMI Corpus

4 Results

5 Discussion

References

[1] Shigeo Abe. Analysis of multiclass support vector machines. *Thyroid*, 21(3):3772, 2003.

[2] J. Han and B. Bhanu. Individual recognition using gait energy image. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 28(2):316–322, February 2006.

[3] Liang Wang, Tieniu Tan, Huazhong Ning, and Weiming Hu. Silhouette analysis-based gait recognition for human identification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(12):1505–1518, December 2003.