Hidden Markov Models for Biometrics

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Introduction

Biometrics is the study of quantitative measurements taken from people.

- They can be useful for identity recognition
- Examples of biometric modalities for recognition are: fingerprints, iris scans, face recognition

A novel biometric modality is based on the measurements from a laser Doppler vibrometer (LDV) aimed at the site of the carotid artery on the neck.

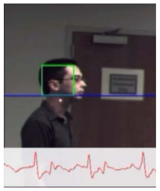


Figure 1. An example signal from the LDV system with an operational photograph. The laser is aimed at the carotid artery along the neck.

Problem Statement

Internal dynamic factors affect the measured LDV carotid pulse.

- Cardiovascular system is in constant flux
- Emotional conditions vary
- Breathing phase impacts cardiovascular state
- These factors presents a significant challenge to the development of a successful biometric system using the LDV carotid pulse.

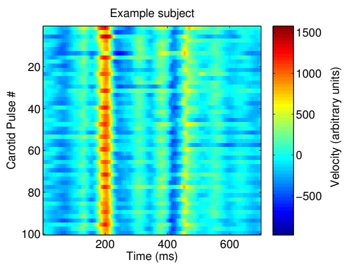
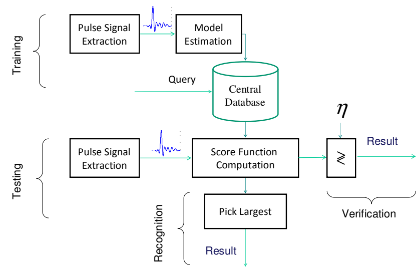


Figure 2. This figure shows a sequence of 100 consecutive LDV pulses.

Method

- One model is estimated for each enrolled individual.
- The score function is the loglikelihood of the query model given the testing data.
- Given testing measurement from an unknown individual, choose the model that maximizes the score function,

$$C_r = \arg\max_m L(x_1, x_2, \ldots, x_T \mid \lambda_m).$$



Hidden Markov Models

- A hidden Markov model is an unobserved Markov chain seen through a noisy channel
- Model the dependence of the LDV pulse on internal factors- the collection of which we call the state.

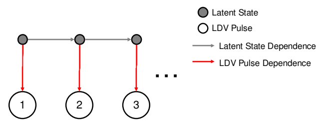


Figure 4. Latent state HMM.

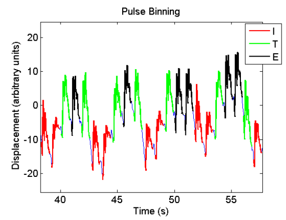


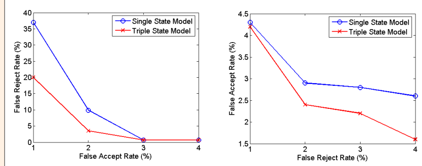
Figure 5. Example of the binning procedure used to initialize the EM algorithm.

Results

- Verification tests were performed on 142 individuals from one recording session, with separate training and testing data.
- Accept or reject decision is made based on the claimed identity, the measured data, and the stored model for the claimed identity
- A null model is used, which represents the "average" individual, and a loglikelihood ratio is formed between the query model given the testing data and the null model.
- Compare the result to a threshold.
- Empirical false reject and false accept error rates (FRR, FAR),

$$FRR = \frac{\#\ of\ individuals\ falsely\ rejected}{I}, \quad FAR = \frac{\#\ of\ individuals\ falsely\ accepted}{I^2 - I}.$$

- Recognition based on most likely individual.



	Number of correctly classified individuals	Recognition performance
Single state	118	83.1%
Triple state	140	98.6%

Conclusions

The HMM based system outperformed the baseline model in all tests. Methods for identity recognition that are dependent on physiological traits may have several advantages over ones that are not affected by crucial physiology:

- They are difficult to counterfeit, because they are related to crucial body function.
- The existence of the biometric marker can be guaranteed.
- They may provide useful supplementary information relating to factors such as stress and health in addition to information used principally for identity verification and recognition.

Comments & Future Work

Several modeling issues were not considered in this work, including (see references):

- The number of states may be variable and chosen according to a model selection criterion.
- Shorter time frames (perhaps 20 ms – 100 ms) may be used to capture faster changes.
- Processing of the data (spectrum, cepstrum, etc.) may lead to decreased error rates with these models.

Improving performance across sessions may involve the following:

- Investigating the physical causes of the observed changes in the signal over long periods of time.
- Determining which components of the signal are stable across sessions.
- Considering whether or not additional information, collected during training or testing, can improve performance.

More questions:

- How does the recognition performance change with the enrollment size?
- How do modeling inaccuracies affect the error rate?

References

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Acknowledgments

The authors would like to thank the following people for valuable assistance in this work: Po-Hsiang Lai, Mei Chen, Sean D. Kristjansson, and Kenji Truman

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