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ACOUSTIC DOPPLER SONAR FOR GAIT RECOGNITION

Kaustubh Kalgaonkar[†] Bhiksha Raj[‡]

[†] Georgia Institute of Technology, Atlanta, Ga 30332

[‡] Mitsubishi Electric Research Laboratories, Cambridge, MA 02139

Abstract

A person’s gait is a characteristic that might be employed to identify him/her automatically. Conventionally, automatic techniques for gait-based identification of subjects employ video and image processing to characterize gait. In this paper we present an Acoustic Doppler Sensor (ADS) based technique for the characterization of gait. The ADS is a very inexpensive sensor that can be built using off-the-shelf components, for under \$20 USD at today’s prices. We show that remarkably good gait recognition is possible with the ADS sensor.

1. INTRODUCTION

“Gait” is defined as a person’s manner of walking. In her seminal studies, Murray [1] proposed that the totality of a person’s gait, including the entire cycle of motion, is a unique and identifying characteristic. In another early study, Johansson [2] attached lights to the joints of human subjects and demonstrated that observers could recognize the subjects from just the moving light display.

In this paper we deal with the topic of *automatic* identification of subjects through observation of their gait (we will generically refer to this topic as “gait recognition”). Gait is by nature a very variable phenomenon, affected by varied factors such as the attire of the subject, the speed of walking, or even their state of mind [12], making it generally difficult to recognize automatically. Even in the best scenario where the subject is walking with a measured regular stride, gait recognition can be affected by the view point and the orientation of the sensor used to take measurements.

Traditionally, the identification of gait has been considered a visual phenomenon – it is a characteristic of a person that must be seen to be recognized. Correspondingly, most current algorithms for automatic identification of gait work from visual imagery, such as video or image data. The procedure typically begins by spotting, tracking and obtaining a silhouette of the subject in the field of view.

A set of features are then obtained from the silhouettes. “Model-based” feature extraction methods impose human-like structures, that are represented as stick models (e.g. [3], [4]), ellipse-based representations (e.g. [5]), etc. Physiologically-motivated features such as joint angles, limb spacing etc. are then derived from the models. “Model-free” feature extraction methods simply attempt to derive features from the silhouettes through a variety of dimensionality reduction methods, e.g. through self-similarity plots [6], Euclidean distances from key frames [7], direct normalization of the silhouettes [8], extraction of additional spatio-temporal representations [9], etc. Recognition of the subject is performed using classifiers such as K-nearest neighbours, HMMs etc.

In the visual paradigm, gait is captured through a sequence of images, each of which represents an instantaneous capture of *static pose*, rather than movement. Any measurements of movement must be deduced from the sequence of poses. An alternative approach to gait recognition does not use visual information, but captures gait-related *motion* (rather than pose) directly through a continuous wave (CW) radar [10] [11]. A high-frequency EM tone is incident on the walking subject. The motion of the walker induces a Doppler shift in the frequency of the reflected tone, which is detected at a sensor. Thus, rather than instantaneous pose, the CW radar captures instantaneous *velocities* of moving body parts.

Conventional wisdom is that high frequencies, such as those used in radars, are required for adequate Doppler-based measurement of the low velocities that compose gait-related motion. In this paper, we present an *acoustic* Doppler based gait recognition system that works from low-frequency ultrasonic tones, rather than EM radar. The device can be built at very low cost using off-the-shelf acoustic devices and low-frequency audio-range sampling. We demonstrate that the proposed mechanism can provide highly accurate gait recognition, even using only simple signal processing schemes that are conventionally employed for radio communication, and an equally simple Bayesian classifier.

The paper is organized as follows section 2 describes the Doppler principle underlying the proposed ultrasonic sensing mechanism for gait. Section 3 describes the acoustic Doppler sensor (ADS) used, Section 4 describes the signal processing used to extract measurements from the signal captured by signal and Section 5 presents experimental evidence of the effectiveness of the device. Section 6 discusses the benefits and limitations of the ADS as compared to the traditional techniques.

2. THE DOPPLER EFFECT AND GAIT MEASUREMENT

The Doppler effect is the phenomenon whereby the frequency of a wave that is perceived by an observer who is moving relative to a source is different from that originally emitted by the source. So also, if the source and observer are collocated and the emitted wave is reflected by a moving target, the frequency of the reflected signal perceived by the observer is different from that originally emitted. Specifically, if a sound source emits a frequency f that is reflected by an object moving with velocity v with respect to the emitter, the frequency \hat{f} sensed by a listener collocated with the emitter is shifted with respect to the original frequency f , and is given by

$$\hat{f} = \frac{v_s + v}{v_s - v} f \approx \left(1 + \frac{2v}{v_s}\right) f, \quad (1)$$

where v_s is the speed of sound in the medium. The approximation to the right in Equation (1) holds true if $v \ll v_s$. If the signal is

reflected by multiple objects moving with different velocities, the signal that is sensed will contain multiple frequencies, one from each object.

A human body is an articulated object, comprising a number of rigid bones connected by joints. Figure 1 illustrates this through an articulated model of various poses of a human walking. During the act of walking the structure moves cyclically from peak stride, where most parts are moving at the overall velocity of the walker (and have minimal velocity relative to one another), to midstride, where the left arm and leg may be moving in opposition to the right arm and leg. From the perspective of an observer directly ahead of the walker, the velocities of the various parts would appear to vary cyclically, where the amplitude of the cycles depends on the distance of the part from its “hinge”. For instance, the velocity of the foot would be observed to undergo larger swings than a point just below the knee.

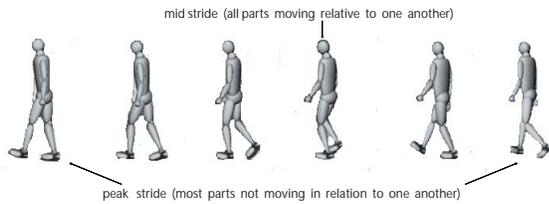


Figure 1: Articulated model of a walking person

When a continuous tone is incident on a walking person, the reflected signal contains a spectrum of frequencies arising from the Doppler shifts of the carrier tone by the velocities of various moving body parts. Figure 2 shows the spectrum of the reflected signal obtained at peak and mid strides when a 40kHz ultrasonic tone is incident on a walker. As expected, at peak stride, the reflected signal shows a relatively narrow band of frequencies with a distinct peak representing the average velocity of the walker. A second peak representing the reflection of the carrier frequency from other static objects is also observed. At mid stride all parts of the body are moving with respect to one another and the reflected signal shows a wider range of frequencies without a clear peak besides the reflected carrier signal.

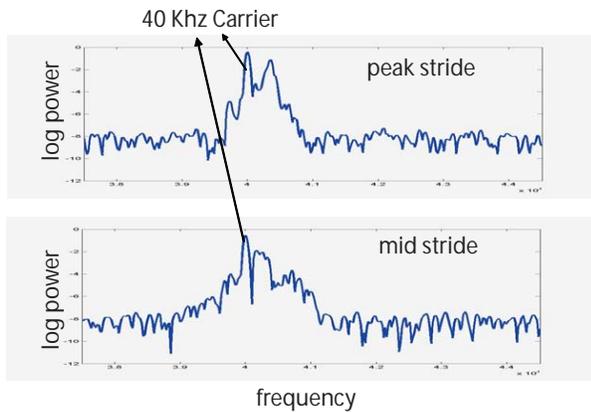


Figure 2: Doppler spectra of peak and mid stride

Figure 3 shows spectrographic representations of reflections of a 40kHz tone incident on two walkers, as they walk toward and away from the ultrasonic sensor. In the figures the horizontal axes represent time, the vertical axes represent frequency and the colour at any point represents the energy of the signal at that time and frequency. The figures thus show how the spectra of the reflected signals change as a function of time. We observe cyclic patterns in the spectrograms. Each cycle represents a stride.

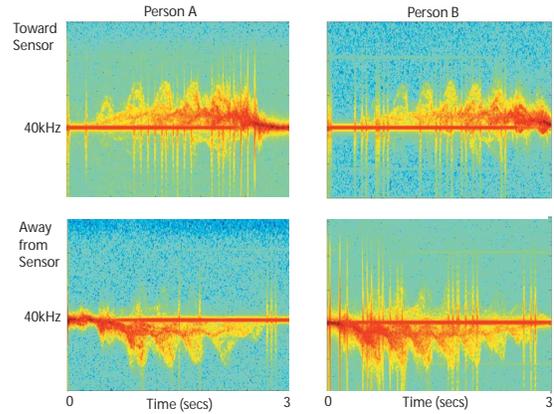


Figure 3: Doppler spectrograms for two walkers. Top left: Walker A walking towards sensor. Bottom left: Walker A walking away from sensor. Top right: Walker B walking towards sensor. Bottom right: Walker B walking away from sensor.

The patterns observed in the spectrograms in figure 3 are typical of the walker. The spectrograms for both walkers exhibit similar cyclic behavior, but the energy distribution in spectrograms are very different. This difference results from the physical characteristics of the individuals and the rate at which their articulators move – these physical features are responsible for induced the Doppler shifts in the reflected signals. It is this difference in Doppler spectral signatures that we utilize to identify the walker.

3. THE ACOUSTIC DOPPLER SONAR

We utilize the Doppler effect of gait on ultrasound signals to identify walkers. Our “acoustic Doppler sensor” (ADS) is built primarily from off-the shelf components and may be plugged into the sound card of any standard PC for signal capture. The entire device can be constructed for less than \$20 in the lab.

Figure 4 shows the block diagram of the acoustic Doppler device we use for gait recognition. It comprises an ultrasound emitter, an oscillator and an ultrasonic sensor. In our setup, the emitter is an off-the shelf MA40A3S ultrasound emitter with a resonant frequency of 40kHz. The oscillator is a PIC10F206 microcontroller that has been programmed to produce a square wave with a duty cycle of 50% on one of its pins. Since the emitter is highly resonant, it produces a nearly perfect sinusoid even when excited by a square wave. The receiver is an MA40A3R ultrasound sensor that can sense frequencies in a narrow frequency band around 40kHz, with a 3dB bandwidth of less than 3000Hz. The relatively narrow bandwidth of the sensor ensures that it does not pick up out-of-band noise. The signal captured by the sensor is multiplied

by a 36kHz tone, also produced by a PIC microcontroller. Multiplication may be achieved programatically using the PIC processor itself, or through a separate analog multiplier. Signal components outside the 0-8kHz range in the multiplied signal are filtered out by a low-pass filter. The low-pass filtered signal is then fed to the sound card of a PC for signal capture. In practice, the low pass filter shown can be omitted since most sound-cards have an anti-aliasing filter that can take care of removing the high frequency components.

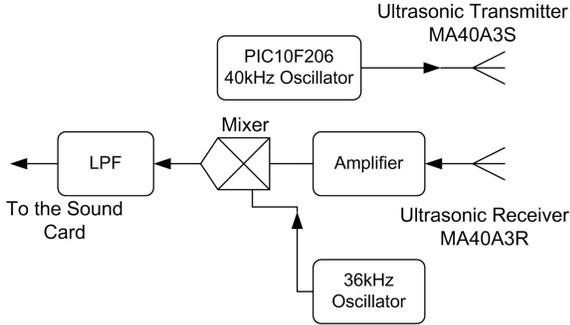


Figure 4: The Acoustic Doppler Sensor

The device is set up such that the emitted ultrasound tone is incident directly upon the walker, at about waist height. The reflected signal (the ‘‘Doppler signal’’) is captured by the ultrasonic sensor. The gait-related Doppler-shifted frequencies in the received signal lie mainly in the $40\text{kHz} \pm 2\text{Hz}$ range. The narrow-band receiver automatically attenuates frequencies outside this range. The signal is heterodyned down to a centre frequency of 4kHz by the multiplier and low-pass filter, and finally sampled at 16kHz at 16-bit precision.

The MA40A3S transmitter has a diameter that is approximately equal to the wavelength of a 40kHz tone and has a beamwidth of about 60° . Targets outside the beam are not sensed through direct reflection. The MA403R sensor also has a similar beamwidth further reducing the effect of reflections from objects outside the beam. The range at which reliable readings may be obtained depends on level of the voltage used to drive the PIC processor (and thereby the voltage level of the 40kHz signal generated by it). With a voltage level of 5V, we have been able to obtain reliable Doppler readings from distances of up to 15m. Greater ranges may be obtained using oscillators that can generate signals of higher peak-to-peak voltage. As the range increases, readings may however be corrupted by the incidental movement of other objects within the beam.

4. GAIT RECOGNITION

In order to recognize a subject from Doppler measurements of their gait, we follow a two-step process. In the first signal-processing step we compute a set of ‘‘features’’ from the Doppler signal. In the second we classify these features using a Bayesian classifier. We describe both steps below.

4.1. Signal Processing

The spectrographic representations shown in Figures 2 and 3 can, in fact, be viewed as *velocity spectra* of a subject’s gait. Each frequency in the signal represents the Doppler shift of the carrier frequency by a specific velocity. The energy in the frequency component is the sum energy of reflections from all body parts moving at that velocity. The spectrogram thus has all the information relating to the patterns of gait-related velocities of a subject’s limbs. In earlier EM-radar-based approaches to gait recognition [11], (transformations of) the spectral vectors comprising the spectrogram have themselves been directly used as characterizations of gait. However, for the acoustic Doppler sensor, we find that that direct characterization of these spectra as features does not result in the best gait recognition. Better performance is obtained by *demodulating* the captured Doppler signal to emphasize the contribution of various velocities.

We note that the Doppler signal is, in fact, the sum of several frequency modulated signals – each moving body part modulates the frequency of the incident tone according to its velocity. We therefore demodulate the Doppler signal using a standard procedure for FM demodulation, comprising differentiation and AM demodulation of the signal. The effect of the demodulation may be explained as follows.

If we model the walker’s structure as consisting of N moving parts, such that the i^{th} part has a time-varying velocity v_i , the signal $d(t)$ sensed by the receiver is the sum of the reflections from all parts and can be written as :

$$d(t) = \sum_i a_i \sin \left(2\pi f_c \left(t + \frac{2}{v_s} \int_0^t v_i(\tau) d\tau \right) + \phi_i \right) \quad (2)$$

Equation (2) utilizes the approximate form of the Doppler equation given in Equation (1). a_i is the amplitude of the signal reflected by the i^{th} component and is related to its distance from the sensor. Although a_i is also time-varying, the changes are relatively slow compared to the cosine terms. ϕ_i is a phase term representing the relative phase differences between the signals reflected by the various body parts in motion. f_c is the carrier frequency. Note that as a result of the heterodyning in the final stage of the circuit in Figure 4, f_c is in fact 4kHz and not 40kHz.

To frequency demodulate $d(t)$, we differentiate it and amplitude demodulate the differentiated signal by multiplying it by a sinusoid of frequency f_c and low pass filtering it. This process yields $y(t)$:

$$\begin{aligned} y(t) &= \text{LPF} \left(\sin(2\pi f_c t) \frac{d}{dt} d(t) \right) \\ &= - \sum_i 2\pi a_i f_c \left(1 + \frac{2v_i(t)}{v_s} \right) \\ &\quad \sin \left(\frac{2\pi f_c}{v_s} \int_0^t v_i(\tau) d\tau + \phi_i \right) \end{aligned} \quad (3)$$

where LPF represents the low-pass-filtering operation. We have assumed here that the time derivative of a_i is negligible compared to other terms. Note that each velocity-related frequency component of $y(t)$ is no multiplicatively enhanced by the velocity itself.

Traditionally Doppler sensors have been used to track targets (cars, air-planes). In target tracking applications it is usually necessary to extract information about each target, and hence to track all corresponding Doppler shifts. In contrast, here, although we have multiple articulators (arms, legs, hips and various joints) all moving simultaneously, we are not interested in tracking them

individually. Our goal is to use this information collectively to characterize the gait and perform recognition. Thus, although the demodulated signal $y(t)$ actually represents an ensemble of frequency demodulated signals, no further decomposition is required.

The demodulated signal $y(t)$ is segmented into frames of 64ms. The frames are relatively wide due to the slow varying nature of the signal. Adjacent frames overlap by 50%. Frames are tapered by a Hamming window and their Fourier spectra computed through a 1024-point FFT. A 513-point power spectrum is derived from the Fourier spectra. The power spectral vectors are compressed by a logarithm and decorrelated through a Discrete Cosine Transform (DCT) to obtain a *cepstral* vector. Only the first 40 coefficients of the cepstral vectors are retained. Each 40-dimensional cepstral vector is augmented by a 1st order *difference* vector computed as the difference between vectors on either side of it. The resulting 80-dimensional vectors are the final set of feature vectors used to represent the signal.

4.2. Bayesian Classification

We model the distribution of the feature vectors obtained from the Doppler signal for any walker w by a Gaussian Mixture Model (GMM):

$$P(X|w) = \sum_i c_{w,i} \mathcal{N}(X; \mu_{w,i}, \sigma_{w,i}) \quad (4)$$

where X represents a feature vector, $P(X|w)$ represents the distribution of feature vectors for walker w , $\mathcal{N}(X; \mu, \sigma)$ represents the value of a multivariate Gaussian with mean μ and variance σ at a point X , and $\mu_{w,i}$, $\sigma_{w,i}$ and $c_{w,i}$ represent the mean, variance and mixture weight respectively of the i^{th} Gaussian in the distribution for walker w . This model ignores any temporal dependencies between the vectors and models them as iid.

We represent the two cases of the walker approaching and moving away from the sensor separately and model them by separate GMMs. The parameters of both GMMs are learned from a small set of training recordings for the walker using the Expectation Maximization algorithm.

Once the parameters of the Gaussian mixture models for all walkers are learned, subsequent recordings are classified using a simple Bayesian classifier. Let $\{\mathbf{X}\}$ represent the set of feature vectors obtained from a Doppler recording of a subject. The subject is recognized as a walker \hat{w} according to the rule:

$$\hat{w} = \operatorname{argmax}_w P(w) \prod_{X \in \mathbf{X}} P(X|w) \quad (5)$$

where $P(w)$ represents the *a priori* probability of walker w . Typically, $P(w)$ is assumed to be uniform across all subjects, since it may not be reasonable to make any assumptions about the identity of the walker *a priori*. Since separate GMMs are used to model the cases of the subject approaching or moving away from the sensor, the classifier not only identifies the subject but also, implicitly, the direction of their movement.

The simple Bayesian formulation above can also be applied to identify classes of subjects, rather than individual subjects. For instance, one may attempt to identify gender of the classifier. In this case separate GMMs would be learnt for the two genders.

5. EXPERIMENTS

Experiments were conducted to evaluate the proposed acoustic Doppler based gait recognition technique. Data was collected in different settings and locations. This was done to reduce the impact of background scatter and to check what effect it might have on the accuracy and performance of the algorithm. A total of 30 subjects were asked to walk towards and away from the sensor. The distance walked by the subjects was approximately 5m in each direction, at a distance of 2-7m from the sensor. Roughly half of the subjects were female and the rest were male. Subjects varied in height from 1.5m to 1.93m in height.

A total of 20 recordings were obtained from each subject, ten each of the subject approaching and walking away from the sensor. Each recording was approximately 3 seconds long. Half the recordings were used for training and the other half was used for testing. Separate Gaussian mixture distributions were trained for the approach and away cases from the corresponding five training recordings

Although the previous sections of this paper have been presented primarily from the perspective of identifying *individual subjects* through their gait, the same principle can, in fact, be used to recognize *classes* of subjects or motion, simply by learning the distributions for the classes from the ensemble of all training recordings for that class. For the experiments reported here, two additional classification tasks were attempted in addition to subject identification. In the first, a classifier was built to distinguish between approach (subjects walking toward the sensor) and away (subjects walking away from the sensor). In the second a classifier was trained to distinguish between male and female subjects¹.

The results of the classification are presented under the columns titled “FM DEMOD” in Table 1.

The acoustic Doppler sensor is observed to be highly accurate at identifying walkers from their gait, identifying the subject and correctly well over 90% of the time. It is also able to determine if the walker is approaching the sensor or moving away from it. This accuracy can be improved to 100% if we couple classification readings with the reflected energy contours. It is interesting to note that it is significantly better than random at identifying the gender of the walker from the gait.

In a second experiment, cepstral features (inclusive of difference vectors) were derived directly from the spectrum of the Doppler signal, without FM demodulating it. This would correspond to the kind of features used in [11]. The aim of this experiment was to establish the utility of the FM demodulation described in Section 4.1. These results are reported in the columns under “Without DEMOD” in table 1. We note that the results obtained without demodulation are much worse than those obtained when the Doppler signal is FM demodulated, except for the “Approach vs. away” experiment. In this latter case improvements are not to be expected from the demodulation since the classifier mainly identifies whether the bulk of the spectral energy has shifted above the carrier frequency or below it – a pattern that is not modified by the demodulation – rather than the actual spectral contours in the signal.

¹Note that in principle both direction and gender are directly inferrable from the results of the subject identification experiment, since toward and away movements were separately modelled for each subject, and a subject’s identity also includes their gender. However for the experiments reported in this paper, generic classifiers were trained

Table 1: Classification results for acoustic Doppler sensor. The “FM DEMOD” columns show the results obtained with features computed from FM demodulated signals. The “Without DEMOD” columns show results obtained with features derived directly from the spectra of the Doppler signal.

Experiment	No. Evaluated	FM DEMOD		Without DEMOD	
		Correctly Classified	Percent correct	Correctly Cassified	Percent Correct
Walker identification	300	275	91.66	216	72.0
Approach vs. away	300	289	96.33	289	96.33
Male vs. Female	300	242	80.66	206	68.66

6. DISCUSSION AND FUTURE WORK

Our experiments show that the proposed acoustic Doppler based gait recognition mechanism can be surprisingly good at multiple gait-recognition tasks, including fine-resolution tasks such as walker identification and coarse tasks such as recognizing the gender of the walker. The results must however be considered with a caveat – all subjects walked with a normal stride more or less directly towards or away from the sensor. It remains to be determined if the mechanism would be equally effective if the gait mode were to vary (*e.g.* if subjects were to walk hurriedly or run). The tolerance of the sensing mechanism to variations in direction of approach is yet unclear. Since all recordings of a subject were obtained in a single session there was no variation in the clothing of subjects between training and test. The sensitivity of the mechanism to variations in clothing remains to be evaluated.

Regardless we believe that the ADS-based gait classifier is a promising avenue for future exploration. In particular, we hypothesize that Doppler-based gait recognition might be used synergistically with vision-based gait recognition systems since the two are almost complimentary in their capabilities and drawbacks:

1. *Direction of approach*: Vision-based systems works best when the subject is walking in a plane perpendicular to the vector from the subject to the camera, so that the entire range of movement of arms and legs can be captured. Doppler-based systems, on the other hand, are most effective when the subject is moving directly towards the sensor as velocities perpendicular to the vector to the sensor are undetectable.
2. *Background effects*: Vision-based algorithms are highly dependent on the ability to extract and track the silhouette of the subject accurately. Various phenomena such as shadows, the layout of the background, etc. can all affect accurate tracking. On the other hand, Doppler-based devices are relatively insensitive to constant background effects, as these can usually be eliminated as clutter.
3. *Secondary Moving Components in the scene*: Both vision and Doppler-based mechanisms are affected by secondary moving objects in the range of the sensor. However, in vision-based algorithms it is possible to remove secondary objects by tracking and segmenting out the target walker, contingent to the availability and use of a suitable algorithm. It is currently however not possible to isolate secondary motion present in the field of view of the ultrasonic sensor.
4. *Operating Conditions*: Unless the sensor is capable of capturing video in low/no light conditions it is not possible for vision based gait sensor to operate in such conditions. The ADS can however operate in low/no light conditions.

One advantage of the ADS lies in its cost – we estimate that if produced in bulk ADS devices could be manufactured for under

\$5 USD (as of 2007). Their energy consumption is also minimal. Consequently they can be deployed in remote sensing application where recovery of the device may or may not be possible.

One restriction of the ADS is its range. Geisheimer et. al. [10] state that they are able to detect gait at a distances of over 100m using an EM radar. However, by being acoustic in nature, the ADS has a much lower range of the order of 10m. While it is possible to increase its range by increasing the energy of the emitted ultrasonic signal, the exact extent to which it may be extended is as yet unknown.

There is still great scope to improve the performance of the ADS sensor beyond that demonstrated in this paper. Our current models do not utilize temporal patterns in the recordings. By modelling temporal patterns in the spectra explicitly, significantly improved classification may be expected. We currently employ only one sensor. By capturing the reflected signals using multiple separated sensors greater robustness to direction of approach and noise may be expected. We also believe that it is possible to identify multiple subjects walking simultaneously using signal processing techniques such as those in [13]. All of these issues are currently under investigation.

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