

Contactless Person Identification Using Cardiac Radar Signals

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Abstract—Radar systems have been researched for the use of presence detection and contactless vital sign monitoring. However, there exists no established biometrics for remote and unique person identification during such monitoring. Conventional biometrics like fingerprint or iris scan yield the disadvantage that direct contact with the person is needed. This paper explores the possibility of using cardiac radar signals as new biometric parameter for unique person identification. Measurements on different persons are performed using a 24 GHz continuous wave radar system which utilizes the Six-Port technology. An advanced signal processing and classification routine is presented to perform automatic person identification. Among several classifiers, quadratic support vector machines achieve the best performance and reach an overall accuracy of up to 94.6%.

I. INTRODUCTION

In recent years, radar technology emerged as a way to perform presence detection and monitoring [1]. Furthermore, it is used to monitor a person’s vital signs like heartbeat and respiration without the need of direct contact [2]–[4]. This is realized by measuring the vibrations on the thorax of a person due to cardiac activity and the lifting and lowering of the thorax due to respiration. Nevertheless, during monitoring, there is no established method so far to perform unique identification of the person that is observed. Person identification would require the prior extraction of biometric parameters. Biometrics describe unique human characteristics which can be used for automatic and unambiguous identification of a person. In the late 19th century, fingerprints were discovered to be a appropriate metric for this task [5]. Fingerprint sensors for unique person authentication are widespread nowadays and can be found in every modern smartphone or notebook. A huge range of alternative biometrics are already in use or are still under investigation. Iris recognition for example is implemented in devices or systems that require a high level of security. Algorithms can detect features in iris patterns to allow for high confidence unique person identification [6]. Besides these already widespread implementations, new biometrics are currently under research. These approaches use different unique physiological characteristics of humans like the signals obtained from an Electroencephalograph (EEG) [7], [8] or the breathing sounds of a speaker [9].

Nevertheless, all above mentioned biometrics have one commonality: the signals have to be measured in direct contact with the person. To identify a person remotely when performing radar presence detection or vital sign monitoring, new biometric features are needed. Radar signals obtained from vital sign observation contain two components, respiration and heartbeat. In [10] and [11], a new biometric feature based on the shape of radar measurements of respiration is presented. Three different features are extracted from the respiration component of the radar distance signal. However, respiration can be controlled consciously which restricts its use as biometric signal to a limited extent. The cardiac activity of a person however is controlled by the autonomic nervous system and might prove to be a unique feature for person identification. Although first studies on cardiac radar person recognition have been performed in [12], neither the physiological theory for a unique cardiac pattern have been examined nor were high accuracies achieved so far. This paper presents a comprehensive study on the suitability of cardiac radar signals as biometric variable. Section II investigates the theoretical physiological backgrounds of unique heartbeat patterns in radar signals. The measurement setup that was used to validate the theoretical findings is described in Section III. Results as well as an advanced signal processing and classification routine for automatic person identification are presented in Section IV.

II. PHYSIOLOGICAL CONSIDERATIONS

When measuring the human heartbeat using radar, so-called sphygmograms are recorded [14]. A sphygmogram is the representation of the pressure in an artery. Pressure (ΔP) and volume (ΔV) changes in the arteries are directly related through the volumetric elasticity coefficient E:

\[ E = \frac{\Delta P}{\Delta V}. \]  

(1)

Since the radar measures a varying distance between the antenna and the thorax, the recorded signals correspond to the sphygmograms. These have different shapes and characteristics, depending on which location they are exactly recorded at. The venous pulse wave, which represents changes in pressure of the blood flowing towards the atriurns of the heart, can be usually recorded in an area around the 2nd intercostal space
Fig. 1. The cardiovascular system of the human at the thorax. [13](2L) on the left side (see Fig. 1) [15], [16]. The ventricle pulse wave, a sphygmogram depicting the pressure changes in the left or right ventricle of the heart, is detected in a region around the 4th intercostal space on the left side (4L). However, the pulse waves from left and right ventricle usually overlay which leads to a superimposed signal that is measured. Furthermore, vibrations from the ventricle pulse wave might propagate far enough to partially overlay the venous pulse wave and vice versa. The signal that is recorded externally on the thorax wall is a mixture of these different components. Each component has a higher or lower impact on the characteristics of the combined signal, depending on the location where it is recorded. Additionally, the exact position and angle of the heart in the thorax as well as the anatomy of the thorax itself is a little different for every person due to varying tissue and muscle/fat compositions, leading to different propagation and attenuation characteristics for each component. A unique pattern is expected to be recorded for every person at a fixed position on the chest wall. Radars further amplify the effect of superimposing the different pulse wave components due to the integrating effect by the antenna over a defined area. [14]

III. MEASUREMENT SETUP

All measurements were recorded using a continuous wave (CW) radar system which utilizes the Six-Port technology [17]. CW radars cannot measure absolute distances which, however, is not necessary since only relative distance changes due to heartbeat activity need to be monitored. A system overview is shown in Fig. 2. The radar system consists of the RF front end as well as the back end that processes the baseband signals. MATLAB is used to perform digital signal processing and classification. Furthermore, an Electrocardiograph (ECG) is used as a reference device to validate certain steps in the signal processing routine. Both the radar as well as the ECG signal are sampled synchronously at a sample rate of 2000 SPS. A photo of the RF front end is depicted in Fig. 3.

A signal at 24.17 GHz is generated by a PSG Analog Signal Generator E8257D from Keysight and transferred to the antenna (ATM 41-441-6). The signal is reflected at the thorax and received by the same antenna. Both reference signal and reflected signal are superimposed in the Six-Port structure which is basically a homodyne mixer. Six-Ports have a low hardware effort due to the complete passive structure and a high phase accuracy [17]. A Six-Port consists of two input ports and four output ports. The two input signals are superimposed under four different relative and static phase shifts which are integer multiples of $\pi/2$. The superimposed signals are down-converted into four baseband voltages $B_3...6$ using the ADF6010 Schottky diode detectors from Analog Devices and fed to the back end via SMA cables. These signals form two pairs of differential signals which are orthogonal to each other. The relative phase shift $\Delta \sigma$ between the reflected and the reference signal can therefore be calculated by

$$\Delta \sigma = \arg \{(B_5 - B_6) + j(B_5 - B_4)\}. \quad (2)$$

A vibration of the thorax caused by the beating heart results in a changing phase shift between the reflected and the reference signal. Since the wavelength $\lambda$ is known, the relative distance change $\Delta x$ can be calculated by

$$\Delta x = \frac{\Delta \sigma}{2\pi} \cdot \frac{\lambda}{2}. \quad (3)$$
Four different test persons (two female, two male) were measured to obtain cardiac pulse signals. All measurements were performed in a seated position. In order to focus the antenna on a defined position on the thorax, a laser positioning is used as shown in Fig. 4. Since the signal components resulting from the ventricles are expected to be stronger than the venous pulse wave [18], the antenna was precisely focused at 4L of each person at a distance of around 50 cm. From every person, 20 measurements with a length of exactly five seconds each are recorded by dividing two measurements with a length of 50 s into ten segments each. These data are used to perform classification and person identification. Five seconds provide a length which is long enough to contain several heartbeats and short enough to facilitate quick person identification.

Fig. 4. Photograph of an exemplary measurement. A laser positioning (inside the red circle) is used to ensure a precise positioning of the antenna.

IV. BIOMETRIC IDENTIFICATION USING RADAR

Measurement signals of all four persons are shown in Fig. 5. A fourth order butterworth bandpass filter with cutoff frequencies at 0.75 Hz and 20 Hz is used for all signals as proposed in [14]. The vertical red lines depict the locations of the R-peaks in the ECG signal. The R-peaks represent the exact moment at which the heart is completely electrically excited and the ventricles are about to contract. While the pulse signals for each person show a periodical pattern, certain characteristics differ from person to person. The signal from person one shows a typical ventricle sphygmogram with a dominant systolic peak due to the ventricle contraction right after each R-peak. Person two also has a dominant ventricle pulse wave component. However, a dominant atrial wave component resulting from the contraction of the atriums can be observed right before each R-peak. The pulse signal of person three has a partly dominant atrial wave component right before each R-peak, what stands out though is the split systolic double peak after each R-peak with a higher peak following the lower first peak. The last signal resembles the signal recorded from person one, however, the systolic peak shows a different characteristic.

To automatically classify the measurements as shown in Fig. 5 and identify the person from which the data is recorded, the single heartbeats of one segment need to be extracted and classified. After that, several classification results from one segment are combined to get an overall classification result for one measurement. The first step is to segment each signal into single heartbeat complexes. For this purpose, the minima have to be found that separate two heartbeats. To determine the minimal distance between two such minima, autocorrelation is performed for every signal to estimate the heart rate. The upper plot in Fig. 6 shows the one-sided autocorrelation of the pulse.
signal from person two. The highest peak in a searching range between 0.45...1.45 s is chosen as average interbeat interval between two successive heartbeats for this measurement. This range corresponds to heart rates between 41 ... 133 BPM (beats per minute). The real interbeat interval determined by the ECG is also plotted to verify the correctness of this example. During the subsequent search for the separating minima, the estimated interbeat interval is multiplied with 0.7 and the resulting value is chosen as minimum distance between two minima. The lower plot in Fig. 6 shows the automatically segmented signal. The vertical lines constitute the minima that separate the single heartbeat complexes. By using the minimum distance information it is prevented that local minima are used as boundaries.

To further process the single heartbeat complexes, each segment is resampled to a defined length of 500 samples using a lowpass filter. By resampling each segment to a uniform length, varying durations of single heartbeats due to different heart rates or sampling rates are eliminated. Otherwise, higher heart rates or lower sampling rates would result in shorter heartbeat complexes with less samples while lower heart rates or higher sampling rates would result in longer heartbeat complexes with more samples. By having segments of uniform length, pattern classification can be directly applied to each heartbeat which will be explained in the following. To apply classification for automatic person identification, all heartbeat complexes from all measurements are extracted. Fig. 7 shows a part of the single heartbeat complexes sorted by person. As shown in Fig. 5, each person has different dominant features in the heartbeat signal which together form a complex and unique pattern. To automatically match these patterns to the according person, classification algorithms are needed. Instead of extracting features from those heartbeat complexes, an end-to-end approach is used. Since all heartbeat complexes are already resampled to 500 samples, every sample is used as an input to the classifier. This way, no prior selection or weighting of features is necessary, which otherwise may lead to biased results. To evaluate the performance of different algorithms, a 5-fold cross validation scheme is used which is a standard evaluation method for performance determination [19]. The dataset consisting of all single heartbeats with their according labels is split into five parts whereby 4/5 of the data are used for training and 1/5 are used for testing. This splitting is repeated until every segment has been used for training as well as testing. The resulting accuracies for single heartbeat classification are shown in Table I.

The quadratic support vector machine (SVM) outperforms other classifiers like k-nearest neighbor (kNN), decision trees or bagged trees. It achieves the highest accuracy of 74.2% among all compared classifiers and is subsequently utilized for person identification. SVMs are supervised learning models for binary classification. Unlike other methods, SVMs do not minimize some kind of training error but try to maximize the margin between the data and the hyperplane that separates the data instead. This is achieved by maximizing the distance between the points which are closest to the hyperplane (support vectors) and the hyperplane. Regular SVMs use a linear hyperplane but by employing different kernels, such as a quadratic kernel in this scenario, performance can be increased significantly. Multiclass SVM classification is enabled by using a one-vs-one approach. [20], [21]

The values in Table I show the overall accuracy when identifying a person using single heartbeat complexes only. Nevertheless, the goal is to apply classification on the whole measurements. This way, robustness can be improved by pro-

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Overall Accuracy</th>
</tr>
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<tbody>
<tr>
<td>Decision tree (max. 4 splits)</td>
<td>54.1%</td>
</tr>
<tr>
<td>Decision tree (max. 20 splits)</td>
<td>54.3%</td>
</tr>
<tr>
<td>Decision tree (max. 100 splits)</td>
<td>55.7%</td>
</tr>
<tr>
<td>Bagged trees (30 Learners)</td>
<td>64.0%</td>
</tr>
<tr>
<td>kNN (1 neighbor)</td>
<td>65.4%</td>
</tr>
<tr>
<td>kNN (10 neighbor)</td>
<td>57.7%</td>
</tr>
<tr>
<td>kNN (100 neighbor)</td>
<td>52.7%</td>
</tr>
<tr>
<td>SVM (Linear)</td>
<td>68.8%</td>
</tr>
<tr>
<td>SVM (Quadratic)</td>
<td>74.2%</td>
</tr>
<tr>
<td>SVM (Cubic)</td>
<td>71.7%</td>
</tr>
</tbody>
</table>
Heartbeat (HB) Boundaries

<table>
<thead>
<tr>
<th>Distance</th>
<th>Accuracy (%)</th>
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<tr>
<td>0.5</td>
<td>−100</td>
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<tr>
<td>1.0</td>
<td>70</td>
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<tr>
<td>2.0</td>
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<tr>
<td>5.0</td>
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Measurement length (s)

<table>
<thead>
<tr>
<th>True Class/Person</th>
<th>Predicted Class/Person</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1  3  4</td>
</tr>
<tr>
<td>2</td>
<td>0  1  2</td>
</tr>
<tr>
<td>3</td>
<td>0  1  2</td>
</tr>
<tr>
<td>4</td>
<td>0  1  2</td>
</tr>
</tbody>
</table>

Fig. 8. Exemplary classification of a five second measurement from person two. The vertical lines show the extracted heartbeat boundaries. Only heartbeat complexes which are fully visible in the measurement will be classified. The thick segments in different colors show the single heartbeats with their according classification result below. The label which occurs most often is chosen as the label for the whole measurement (in this case person two).

Fig. 9. Confusion matrix showing the classification results. 20 pulse measurements obtained by radar from every person with a length of 5 s each are classified using 5-fold cross validation.

Fig. 10. Accuracy in comparison to the length of the measurements: the longer the measurement, the higher the overall accuracy of the classification results.

An overall accuracy of 91.3% is achieved for person identification using measurements with a length of 5 s. Furthermore, all classes have a precision that is higher than 80% and a recall that is also higher than 80%. Fig. 10 shows the overall classification accuracy for different measurement segment lengths. A shorter segment length of 3 s, which results in fewer heartbeats per measurement, leads to a decrease of the accuracy to 78.3%. When choosing an enlarged segment duration of 7 s, more heartbeats are contained in one measurement, increasing the accuracy to 94.6%.

V. CONCLUSION

This paper presented a new approach for contactless person identification using cardiac radar signals. Theoretical considerations on physiological backgrounds have been discussed that lead to a unique heartbeat pattern during remote radar monitoring. A continuous wave radar system has been used to perform measurements on different persons. Investigations on the detected heartbeat signals unveiled two results. On the one hand, signals of one person show a periodical pattern, and on the other hand, signals from different persons differ in certain characteristics. Extracted single heartbeats show that each person has a unique heartbeat pattern. Different classifiers are examined for automatic person identification using a 5-fold cross validation scheme. Quadratic support vector machines achieved the best performance and reach an overall accuracy of 74.2% applied on single heartbeats. Using it on measurements with a length of 5 s, an overall accuracy of 91.3% can be reached. Accuracy can be further increased to 94.6% using a segment length of 7 s.

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REFERENCES