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Published in:
2023 IEEE 32nd International Symposium on Industrial Electronics, ISIE 2023 - Proceedings

DOI:
10.1109/ISIE51358.2023.10228178

Published: 01/01/2023

Document Version
Peer-reviewed accepted author manuscript, also known as Final accepted manuscript or Post-print

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Please cite the original version:
Golipoor, S., & Sigg, S. (2023). Accurate RF-sensing of complex gestures using RFID with variable phase-profiles. In *2023 IEEE 32nd International Symposium on Industrial Electronics, ISIE 2023 - Proceedings* (Proceedings of the IEEE International Symposium on Industrial Electronics; Vol. 2023-June). IEEE. https://doi.org/10.1109/ISIE51358.2023.10228178

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Accurate RF-sensing of complex gestures using RFID with variable phase-profiles

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***Abstract*—We propose the use of clothing-integrated conductive textile-based Radio Frequency Identification (RFID) tags featuring variable-phase profiles for RF-based human sensing. This approach enables the distinction and interpretation of movements from various body parts independently. We propose a scheme based on varying phase profiles in order to isolate reflections from distinct tags. The feasibility of the approach is demonstrated analytically in this work. Our instrumentation in a laboratory environment involves tag-groups attached to a solid board. The next step is the evaluation of the system when tags are mounted to a moving person.**

***Index Terms*—RF-based human sensing, RFID**

I. Introduction

Radio sensing comprises the collection and interpretation of stimuli obtained from electromagnetic radiation regarding location and tracking (Device-free localization) [1], [2], activities (Device-free activity recognition) [3], [4], postures [5], gestures [6], vital signs [7], or emotion [8]. Applications include human-robot collaboration [9], remote health monitoring [10], ambient assisted living [11], surveillance [12], as well as smart-appliance interaction [13], [14].

Environmental alteration leads to changes in the reflection and propagation of electromagnetic signals, which in turn can be measured and interpreted at a receive device [15]. By sending signals that linearly increase in frequency over time (e.g. frequency-modulated continuous wave (FMCW)), the distance and mobility of multiple objects can be identified [6].

Alternative sensing modalities, such as light-based approaches including cameras [16] or Lidar [17] possess properties that make them less favorable in some domains of human-behavior sensing. In fact, certain environmental light conditions may impair their performance (e.g. low light, smoke, or opaque blockage). They further suffer from excessive absorption or scattering of the probing signal during inclement weather or through occlusion. Furthermore, a ubiquitous installation of video systems in public and private spaces usually meets reluctance [13]. Radio-based sensing, on the other hand, is less affected by these aspects. It features a higher abstraction level while still providing satisfactory environmental sensing performance [6].

Device-free RF-based sensing typically exploits changes observed in phase and frequency of reflected signals. For instance, FMCW-type radar systems utilize frequency modulated chirps in order to distinguish direction and distance of movement. However, since a signal component does not contain information from which body part or object it was reflected, the interpretation of the movement inherits uncertainty. This uncertainty necessarily may lead to a lower recognition accuracy.

We acknowledge partial funding by the European Union through the Horizon EIC pathfinder challenge project SUSTAIN (project number 101071179)

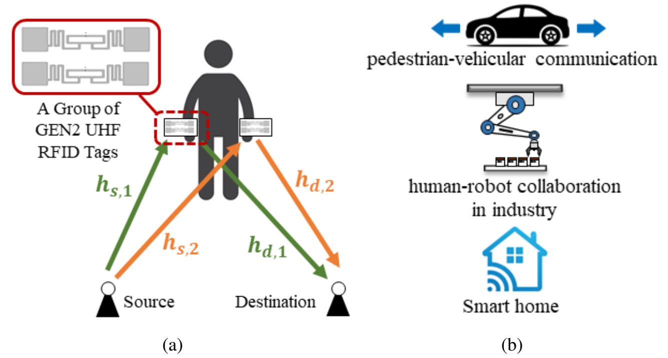

Fig. 1: Conceptual view on the System Model and its applications: (a) Two groups of tags are attached to different body parts of a person. The phase profile by the respective tags are designed to change between two states over time. The superimposed signal at the receiver can be isolated for the respective tag groups given due to the orthogonality of the tag profiles. (b) Potential applications.

A second challenge for radio-based human sensing, as with any environmental human-sensing modality, is the privacy concern. This is because individuals have no means of opting out of being sensed within the coverage of the sensing system.

To overcome both of these challenges, we propose an RF-based sensing system comprised of clothing-integrated conductive textile-based Radio Frequency Identification (RFID) tags featuring variable phase profiles for distinct body parts. This approach enables the distinction and interpretation of movement from various body parts independently and further, since it relies on wearable components, allows subjects to opt-out or to constrain the sensing accuracy by simply not or only partially wearing the reflecting tags.

II. Related Work

Backscattering has been proposed for Internet of things (IoT) applications thanks to their low power and low complexity [18]. This includes the use of commercial Ultra High Frequency (UHF) RFID tags for sensing purposes [19]. Commonly, RFID devices are placed such that they surround an area of interest in which subjects move [20], [21]. Localization of subjects is then determined through information on the blocking of line-of-sight (LoS) paths between the reader and the tags. Furthermore, the angle of arrival (AoA) may be derived [22], as well as the received signal strength and the phase of signals [23], [24].

Furthermore, magnitude and phase of backscattered signals may be used for perception purposes. Hence, the incident power at a tag as well as the impact of geometry of a tag on the received signal strength (RSS) and phase of RFID backscatter signals has been studied [25], [26]. For instance, hand movement has been recognized using an RFID array and applying support vector machine and decision tree classifiers on the magnitude and phase information from backscattered signals [27].

Traditionally, in RFID-based perception and sensing, the tags are scattered in the environment and surrounding a sensing area, while movement of non-equipped subject(s) is detected from the signals reflected from the tags. For instance, the authors in [28] recognize hand gestures conducted in an area surrounded by backscattering tags while in [29] the orientation of the head of a person is recognized from the signals perceived at an RFID tag array. In contrast, we propose to equip the subject with backscattering devices through conductive-fiber RFID tag group structures. By utilizing different phase profiles for the respective tag groups, we are able to then distinguish the movement of different body parts and to process them separately for gesture recognition.

Related to our approach, the authors in [30] embedded RFID tags on gloves and studied hand gesture recognition by interpreting movement patterns with the help of dynamic time warping. Furthermore, the impedance characteristics at wrist-worn antennas have been exploited in [31] for the recognition of hand gestures.

We are not aware of any work exploiting phase profiles of RFID tags for the distinction of signal reflections from various body parts.

III. Phase profiles to detect body-part movement

A challenge in RF-perception for human sensing is that the receiver is usually ignorant about which part of a signal has been reflected by which body part. UHF RFID tags may modify the phase of a signal before backscattering it and this may also follow a pattern of phase offsets over time [32]. Such phase profiles can be utilized to distinguish different tags or tag groups [33]. Using passive UHF RFID tags with distinct phase profiles on different parts of a body, we propose a signal processing scheme in which different parts of human body can be identified separately with radio signals. This concept is similar to marker-based motion recognition systems (e.g. https://optitrack.com/) as it is employed for instance, for body landmark detection in vision-based human sensing [34].

Intelligent surfaces composed of RFIDs are attached on different parts of a body as illustrated in Fig. 1a. Through an appropriate choice of the phase profile patterns and signal processing, we are then able to separate the first surface's reflection path from the second one.

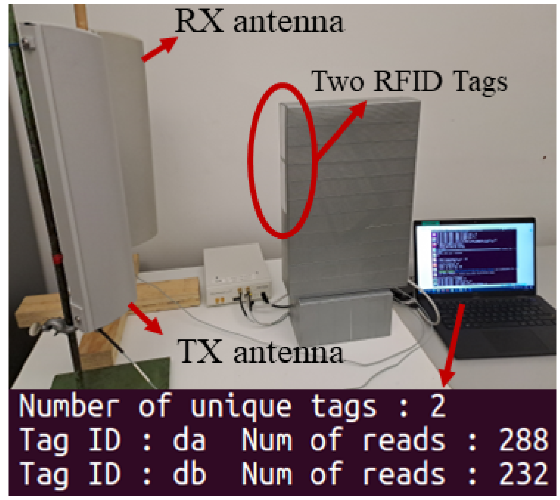

Fig. 2: Setup and identified two unique tags. Software-defined RFID reader was tested using GNU Radio and USRP N200 equipped with a single RFX900 daughterboard and two dipole antennas.

This approach provides a significant privilege over alternative RF-based gesture recognition techniques since RSS and phase can be processed and interpreted separately for different parts of a body. Hence, it enables improved detection of full-body gestures as well as the recognition of new, previously unprecedented gestures via RF-sensing. Potential applications are shown in Fig. 1b. For instance pedestrian-to-vehicular communication through gestures, or human robot interaction. Precise hand gesture recognition also can be employed to control smart homes appliances.

Accordingly, we tested the software developed in [35] to identify two unique Zebra Z-Select 2000T tags using USRP N200 as demonstrated in Fig. 2. In principal, circularly-polarized antennas should be used and since we used dipole antennas, we could detect the tags in about 30cm. We plan to use this software to implement signal processing technique presented in this paper to distinguish reflected signals from different part of body.

IV. System Model

We adapt the following notation: Vectors are columns by default and represented by lower-case bold letters while matrices are described by upper case bold letters. Moreover, $[\mathbf{X}]_i$ denotes the ith row of matrix $\mathbf{X}$. We utilize two groups of RFID tag pairs on the wrists of a person performing a gesture (cf. Fig. 1a). Signals emitted by a single antenna transmitter (source) are then observed, processed and interpreted by the receiver (destination). We assume that no LoS exists between transmitter and receiver. Let $\mathbf{h}_{d,n} \in \mathbb{C}^{1\times 2}$ and $\mathbf{h}_{s,n} \in \mathbb{C}^{2\times 1}$ be the nth[1] group receive and transmit channels, respectively:

$$\mathbf{h}_{d,n} = \begin{bmatrix} h^d_{n,0} & h^d_{n,1} \end{bmatrix} \quad n = 1,2 \tag{1}$$

[1]Without loss of generality, $n \in \{1, 2\}$ for the discussion in this paper.

$$\mathbf{h}_{s,n} = \begin{bmatrix} h^s_{n,0} & h^s_{n,1} \end{bmatrix}^\top \quad n = 1,2 \tag{2}$$

Let $\boldsymbol{\alpha}_{n,t}$ be the phase profile of tag group n at time t so that we can write

$$\boldsymbol{\alpha}_{n,t} = \begin{bmatrix} \alpha_{nt0} & \alpha_{nt1} \end{bmatrix}^\top \quad n = 1,2 \quad t = 0,1 \tag{3}$$

For instance, $\boldsymbol{\alpha}_{2,1} = \begin{bmatrix} \alpha_{210} & \alpha_{211} \end{bmatrix}^\top$ denotes the phase profile of the second group of tags at time 1 and α_{210} and α_{211} are the respective phase sequences produced by the first and second tag in that tag group.

The received signal at time t can thus be represented as

$$y_t = \sum_{n=1}^{2} H_n(\boldsymbol{\alpha}_{n,t})\sqrt{E}x_0 + z_t. \tag{4}$$

Here, x_0 is the transmitted pilot symbol such that $x_0x_0^* = 1$ and its energy is E, while $H_n(\boldsymbol{\alpha}_{n,t})$ is the reflected channel via the n-th group that can be written as

$$H_n(\boldsymbol{\alpha}_{n,t}) = \mathbf{h}_{d,n}\mathrm{diag}(\boldsymbol{\alpha}_{n,t})\mathbf{h}_{s,n}. \tag{5}$$

Furthermore, $z_t \sim \mathbb{CN}(0, N_0)$ represents the complex additive zero-mean white noise.

V. Phase Profile Design of the Tag Groups

At the receiver, the signal components representing the two paths via the respective tag groups are superimposed. We will now describe how the signals received may be separated for their path (green and orange in Fig. 1a) from each other. Specifically, we define the phase profiles of the respective tag groups at time $t = 0,1$ as

$$t = 0: \begin{cases} \boldsymbol{\alpha}_{1,0} = \begin{bmatrix} 1 & 1 \end{bmatrix}^\top \\ \boldsymbol{\alpha}_{2,0} = \begin{bmatrix} -1 & -1 \end{bmatrix}^\top \end{cases} \quad t = 1: \begin{cases} \boldsymbol{\alpha}_{1,1} = \begin{bmatrix} 1 & 1 \end{bmatrix}^\top \\ \boldsymbol{\alpha}_{2,1} = \begin{bmatrix} 1 & 1 \end{bmatrix}^\top \end{cases} \tag{6}$$

In other words, the tag groups alternatingly reflect the signal with differing and then identical phase shift. This is achieved by imposing a continuous alternation of applied phase shifts at one of the tag groups (here group 2). A synchronization between the tag groups is not needed since the first tag group's phase profile remains unchanged over time, while the phase profile of the second group switches between two states.

To achieve signal separation, we also define the Hadamard matrix $\boldsymbol{\Theta}$ as

$$\boldsymbol{\Theta} = \begin{bmatrix} \theta_{1,0} & \theta_{1,1} \\ \theta_{2,0} & \theta_{2,1} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}. \tag{7}$$

We now remove the pilot symbol by multiplying the received signal with x_0^*. Since $x_0x_0^* = 1$, this leads to

$$\begin{aligned} v_t = y_t x_0^* &= \sum_{n=1}^{2} H_n(\boldsymbol{\alpha}_{n,t})\sqrt{E} + z'_t \\ &= (H_1(\boldsymbol{\alpha}_{1,t}) + H_2(\boldsymbol{\alpha}_{2,t}))\sqrt{E} + z'_t. \end{aligned} \tag{8}$$

The signal components v_0 and v_1, obtained via the two signal paths at time 0 and 1 are then[2]

$$\begin{aligned} v_0 &= (H_1(\boldsymbol{\alpha}_{1,0}) + H_2(\boldsymbol{\alpha}_{2,0}))\sqrt{E} + z'_0 \\ &= (\mathbf{h}_{d,1}\mathrm{diag}(\boldsymbol{\alpha}_{1,0})\mathbf{h}_{s,1} + \mathbf{h}_{d,2}\mathrm{diag}(\boldsymbol{\alpha}_{2,0})\mathbf{h}_{s,2})\sqrt{E} + z'_0 \\ &= (\begin{bmatrix} h^d_{1,0} & h^d_{1,1} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} h^s_{1,0} & h^s_{1,1} \end{bmatrix}^\top + \begin{bmatrix} h^d_{2,0} & h^d_{2,1} \end{bmatrix} \\ &\quad \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} h^s_{2,0} & h^s_{2,1} \end{bmatrix}^\top)\sqrt{E} + z'_0 \\ &= (h^d_{1,0}h^s_{1,0} + h^d_{1,1}h^s_{1,1} - (h^d_{2,0}h^s_{2,0} + h^d_{2,1}h^s_{2,1}))\sqrt{E} + z'_0, \end{aligned} \tag{9}$$

$$\begin{aligned} v_1 &= (H_1(\boldsymbol{\alpha}_{1,1}) + H_2(\boldsymbol{\alpha}_{2,1}))\sqrt{E} + z'_1 \\ &= \ldots \textit{(cf. equation (9))} \ldots \\ &= (h^d_{1,0}h^s_{1,0} + h^d_{1,1}h^s_{1,1} + (h^d_{2,0}h^s_{2,0} + h^d_{2,1}h^s_{2,1}))\sqrt{E} + z'_1. \end{aligned} \tag{10}$$

For the extraction of the individual signal components according to the two propagation paths, we combine both in the vector

$$\mathbf{v} = \begin{bmatrix} v_0 & v_1 \end{bmatrix}^\top. \tag{11}$$

The individual signal components u_1 and u_2 (isolated green and orange paths) can then be obtained as

$$\begin{aligned} u_1 &= [\boldsymbol{\Theta}]_1\mathbf{v} = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} v_0 & v_1 \end{bmatrix}^\top = v_0 + v_1 \\ &= 2(h^d_{1,0}h^s_{1,0} + h^d_{1,1}h^s_{1,1})\sqrt{E} + Z_1, \end{aligned} \tag{12}$$

$$\begin{aligned} u_2 &= [\boldsymbol{\Theta}]_2\mathbf{v} = \begin{bmatrix} -1 & 1 \end{bmatrix} \begin{bmatrix} v_0 & v_1 \end{bmatrix}^\top = -v_0 + v_1 \\ &= 2(h^d_{2,0}h^s_{2,0} + h^d_{2,1}h^s_{2,1})\sqrt{E} + Z_2. \end{aligned} \tag{13}$$

Our implementation evaluates this signal processing technique for device-free RF-based gesture recognition. As illustrated in Fig. 3, in particular, we will extract features such as phase and RSS for each separated signal component and then derive an optimal classification algorithm for gesture recognition on this data.

For the sake of simplicity, we have introduced the scheme with two tags on each hand. However, without loss of generality, more RFID tags can be employed in each group and also more tag groups can be designed in order to cover further body areas. This approach will greatly improve the signal representation as can be seen from equation (12) and equation (13).

VI. Conclusion

We have presented an approach for the distinction of different body parts in RF-sensing applications, which allows for previously unprecedented accuracy. Implementation of the signal processing scheme will provide separation of different human body parts in the radio frequency domain using UHF

[2] We assume that channel parameters are constant during time 0 to 1 since the phase profile is altered significantly faster than the movement speed of the monitored subject.

Fig. 3: Gesture recognition utilizing distinct phase profiles of backscatter tag groups attached to various body parts requires as a first step the processing of the signals to isolate individual signal paths (this paper). Then, standard feature extraction and classification pipelines are applied on the respective signal streams of distinct body parts.

RFID tags. By separating received signals from different part of a body, an application may distinguish the movement of various body parts independently and thus even construct a body skeleton. From these isolated reflected signals, relevant features, such as RSS and phase for various gestures can be analysed and trained.

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