

Machine Learning with Wearable RFID Grid for Monitoring Fetal Movements

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Abstract

Fetal movements are crucial signs of the fetus' well-being and are clinically monitored with self-reports or wearable detectors. However, wired detectors worsen mothers' labour, and wireless ones are still not adopted due to their higher cost. Radiofrequency identification (RFID) can be exploited to develop low-cost solutions for detecting fetal movements based on tag response variations. In this contribution, a wearable RFID grid for fetal monitoring is manufactured and tested. Even though the backscattered EM wave unpredictably changes when tags are displaced by a probe emulating a foot of a 20-week-old fetus, a decision tree for classification detected motionless and moving tags with accuracy $> 91\%$ in the preliminary test.

1 Introduction

Fetal movements are signs of a fetus' well-being directly observable by mothers and physicians, usually from the 20th week of gestation. The absence of such movements can indicate fetus is suffering and must be cared for to preserve it from stillbirth. Mothers can follow several procedures to assess fetuses' health based on the number of perceived movements; for instance, a healthy baby should move ten times in 30 minutes when awake [1]. However, self-reporting by the mother is prone to errors, especially if she is anxious about her baby's health [2]. Instruments measuring the number of movements are hence used for medical checks, particularly right before the birth of the newborn [2]. Classical wired devices like cardiocographs are highly uncomfortable for the mother during labour, though, and wireless devices are still little employed due to their higher cost [2], so developing novel solutions is a current research topic [3,4].

A low-cost wireless solution could be achieved by radiofrequency identification (RFID) technology. RFID was successfully tested for sensing little movements based on the strength and phase of the backscattered wave [5]-[7]. This contribution proposes, for the first time, a wearable grid of RFID tags and an ML algorithm to monitor fetal movements (Figure 1(a)). Given that embryos and fetuses are sensible organisms that must be protected from EM exposure [8], a shielding conductive layer between the tags and the mother is needed to protect the mother and unborn from harm. The presence of the conductive layer and the variable inter-tag coupling during movements, in turn, are expected to alter the responses from the tags unpredictably. Machine learning (ML)



Figure 1. (a) Concept of the RFID system for monitoring fetal movements. (b) A woman in the 24th week of pregnancy wearing the ground plane of the grid.

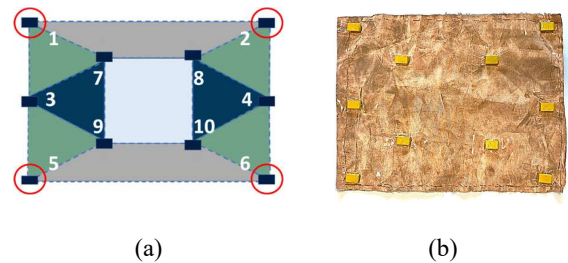


Figure 2. Manufacturing of the RFID grid. (a) The layout of the grid, the geometrical tessellation of the area to be monitored, and the tags' numbering. Tags (1,2,5,6) cannot be moved and are circled in red. (b) Prototype of the RFID grid.

techniques will be hence necessary to exploit the complex relationship between fetal movements and the EM data [6],[7],[9]. In the following pages, the RFID system is described and characterized. Then, the utilized ML technique is introduced, and preliminary experimentation with a rounded cylinder emulating the foot of a fetus is detailed.

2 RFID System

2.1 System Description

The RFID system is constituted of a reader and a grid of tags continuously monitoring the mother's abdomen while protecting the fetus from radiofrequency power. The RFID grid employs a copper thread (thickness: 1.4 mm) to shield the mother's abdomen from the interrogating field, and the tags are fixed onto the shielding tissue.

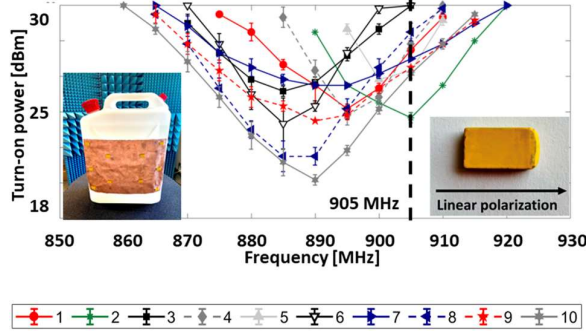


Figure 3. Turn-on power of the RFID grid when fixed to the homogeneous liquid phantom. In the left inset: the RFID grid on the liquid phantom. In the right inset: zoomed-in view of one RFID tag of the grid and its polarization.

Based on [10], an area of 25 cm x 20 cm is suitable for covering one whole side of the uterus (Figure 1(b)). The grid prototype investigated here covers such an area, even though a more extended ground plane should be used in future to avoid border effects and currents flowing on the copper thread. Ten tags for on-metal applications (PQS-SR-03 by PQSense, which are folded patches with a ceramic substrate) are attached to the copper tissue to cover the entire area according to regular geometrical shapes (Figure 2(a)). The tags are linearly polarized like the reader's antenna (log-periodic antenna AN-FF-WB by Voyantic) so that polarization losses are minimized. The copper thread and the medical tape (Tegaderm by 3M) used for fixing the tags are breathable materials optimal for wearable applications. Figure 2(b) shows one prototype of the RFID grid. The interrogation software used for the experimentation reported next can interrogate the entire grid in about one second so that a dataset of 18,000 responses can be created during the 30 minutes usually employed for monitoring fetal movements.

2.2 EM Characterization

The grid is characterized by tags' turn-on powers (P_{To} ; the minimum power the reader has to generate to obtain a response from the tag) when the reader antenna is placed at a safe distance from the mother. According to [8], RFID readers should be distant from the mother ≥ 50 cm and placed on the coronal anatomical plane of the mother; consequently, 50 cm between the center of the phase of the reader's antenna and the grid's center was the distance used to characterize the grid. P_{To} was measured (reader: Tagformance by Voyantic) when the grid was attached to a liquid phantom emulating human tissue (dielectric permittivity $54 + j21$, conductivity 1.05 S/m, by SPEAG). Despite differences in the P_{To} values due to the different positions, border effects, and the variability between the commercial-off-the-shelves tags, all tags have $P_{To} \leq 30$ dBm at 905 MHz, so that was the operating frequency investigated (Figure 3).



Figure 4. Picture of the grid interrogation while one tag was displaced to reproduce a kick of a 20-week-old fetus. In the inset: the cylindrical probe which reproduces the fetal foot.

3 Preliminary Experimentation

The RFID grid should detect fetal movements through changes in the RSSI and phase from the tags when they are worn by the mother and are continuously queried by the reader. Movements are expected to modify the distance between the grid and the reader, the EM coupling between the tags, and the reflections caused by the copper tissue. In this preliminary investigation, the reference case when the deformation happens right under one mobile tag is explored.

To observe the effects of the movements on the tags' responses, a cylindrical probe simulating the movements of a 20-week-old fetus was manually moved when recording the timing of the movements [3]. The wooden scaffold kept the grid in place while a displacement of 10 mm was imposed for 3 seconds right under the tag, reproducing the movement of such a fetus [3] (Figure 4). The responses of the ten tags were recorded by custom software piloting an M6e reader (by ThingMagic). The tags number (1,2,5,6) were fixed to the wooden scaffold and were not moved since those tags should be used as reference points to monitor the eventual movements of the mother, which are not considered yet in this investigation. Five movements per tag were completed using the cylindrical probe in sessions of 75 seconds.

Figure 5 reports the responses of the six mobile tags when the deformation is impressed right under the tags; for the sake of visualization, the contemporary responses of the other nine tags are not plotted. It is evident that the tags' responses change when the cylindrical probe touches the grid, yielding abrupt variations of the RSSI and/or the phase (Φ).

4 Decision Tree for Movements Detection

Since no trivial relationship between the EM tracks and the movements to be counted exists, ML was exploited to discriminate responses by moving tags from those by

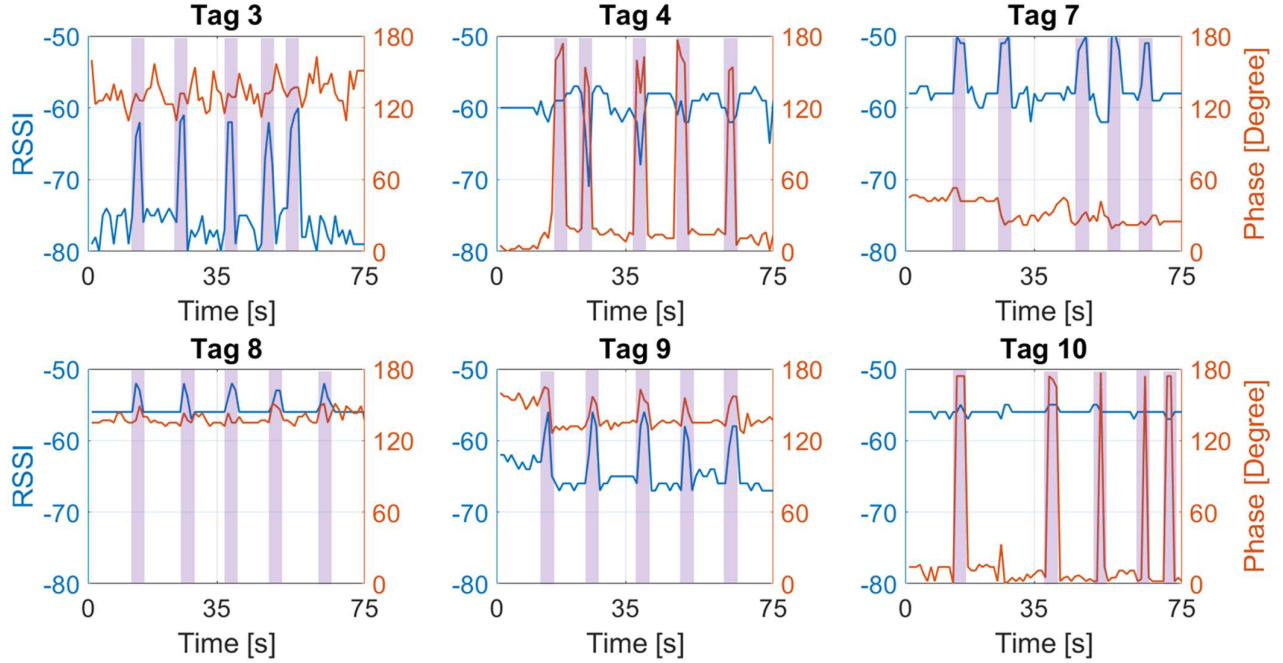


Figure 5. The response of the six mobile tags during their respective 75-second-long session. Vertical rectangles indicate when the displacement of the tag is impressed.

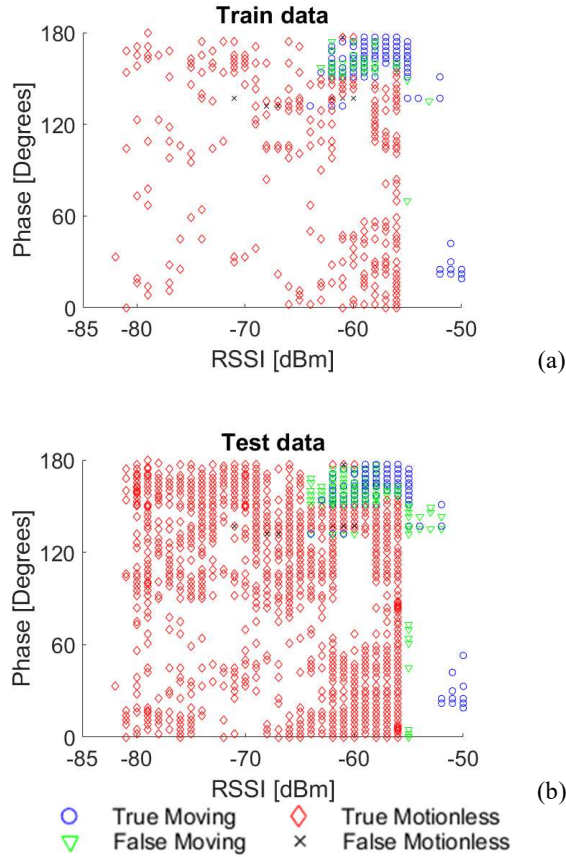


Figure 6. Performance of the decision tree on the feature's plane during (a) training and (b) test.

motionless tags. Among several possible techniques, a decision tree was trained for its easy implementation and integration with standard software for RFID [9]. Decision trees are supervised algorithms splitting data according to conditional relationships that the machine learns based on the training phase. Their strengths include the capability of dealing with data of different natures and the easiness of visualization, whereas their primary liability is a high sensitivity to changes in the training dataset, limiting their predictive power [11]. The features' space is thus divided into two sub-spaces at each decision until classification is achieved. Given a threshold T and the XOR operator (∇), conditional relationships will hence be expressed in the form

$$[RSSI \nabla \Phi] \geq T. \quad (1)$$

By considering the pair $\{RSSI, \Phi\}$ of each response obtained during the grid interrogations as an input, the overall gathered dataset is composed of 4230 data, of which 429 were collected during a movement (class 1 for the classifier to be trained). 80% of the 429 responses were used for training, and the dataset was balanced, yielding a training dataset of 858 $\{RSSI, \Phi\}$ pairs. The tree was trained using the labelled dataset through MATLAB R2019b and verifies conditions on RSSI or Φ without considering any combination of them. The training dataset was extracted from all the data casually.

The tree was validated using K-fold cross-validation where the training set is divided into K subset and, for each

iteration of training, $(K - 1)$ subsets are used to obtain a classification tree, while the remaining subset is used to compute the efficiency. $K = 10$ was used since this value returns a conservative estimate of the algorithm performances if the training set represents the phenomenon fully [12]. A five-layer tree classifying the input based on six conditional relationships maximum returned the best performance on the training dataset, reaching 96.1% of correct classifications (Figure 6(a)).

After training, the decision tree was tested on the whole dataset. The machine still achieves reliable performance, and 91.8% of the data is classified correctly (Figure 6(b)). Thanks to the ML approach, it is possible to exploit the complex relationship between the variations of the EM response and the tag's movement. From the scatter plots in Figure 6, it is evident that most errors are false positives; namely, a movement is detected when the tag is stationary. This limitation of the classifier is due to the training dataset not representing class 1 adequately so that a more balanced training set, tags designed to have sharper $\{RSSI, \Phi\}$ variations (e.g., highly-directive radiation patterns), as well as more sophisticated ML techniques, can achieve higher accuracy.

5 Conclusion

A wearable RFID grid for counting fetal movements through ML was manufactured and tested. All the tags of the grid can be continuously interrogated without posing any risk to the health of the mother or the baby, thanks to a copper tissue acting as an EM shield. A decision tree was then trained and tested over the responses gathered through a cylindrical probe that reproduces the movements of a fetus 20 weeks old. The decision tree achieved an accuracy higher than 91% in detecting the movement of a tag, even if the displacement was as short as 10 mm. The feasibility of employing RFID grids for monitoring fetal movements was proven, and the accuracy of the system can be increased further by exploiting the entire recorded tracks of all the tags and their relationships instead of individual $\{RSSI, \Phi\}$ pairs. Furthermore, future works can improve the preliminary system by designing optimized tags for the grid, employing a broader ground plane and more tags, and testing the sensing capabilities of the grid.

Acknowledgements

The authors thank Ms Giulia Veltro and Mr Tommaso Maria Bianco for their help during the grid manufacturing.

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