A phase-based technique for discriminating tagged items moving through a UHF-RFID gate

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***Abstract*—A phase-based technique is presented for discriminating tagged items moving on a conveyor belt from other tagged items that are present in the scenario, when a UHF RFID gate is installed at a conveyor section. Indeed, tagged items (either static or randomly moving in the scenario) that are close to the reader antenna could be detected even if they are not on the conveyor (false positive readings). The classification procedure here proposed is based on some features that are extracted from a phase-based technique used to localize tags on a conveyor belt, which takes advantage of the fact that the tagged items move along a conveyor whose speed and path are both known *a priori*. Differently from other techniques that are used to solve the above misclassification issue, the proposed approach does not require multiple antennas.**

***Keywords*—UHF RFID systems; phase-based radiolocalization; moving tag; static tag.**

I. INTRODUCTION

In the last years, the RFID technology is gaining increasing interest for item level tagging in logistic applications [1]-[2]. Specifically, the UHF RFID systems allow for a remote identification without requiring proximity coupling (as needed for bar code readers and HF RFID tags), with the advantages of a low-cost deployment, compact tags and high read rates. A large number of tagged items can be contemporary managed and the service process can be faster. Often, in supply chains, the goods in transit in the warehouse are detected by a UHF RFID gate, namely an identification point equipped with a UHF RFID reader and one or more antennas. Due to the large beamwidth of typical reader antennas and the multipath effects typical of a crowded indoor scenario, both tagged items moving along a conveyor belt and passing through the gate, as well as static tagged items located all around the scenario can be identified during the same inventories. However, a right classification of all the detected tags is mandatory for a correct goods management, and the false positives issue must be solved. In [3], a probabilistic model based on a discrete Hidden Markov Model (HMM) has been proposed. The tag behavior during its movement through the gate is described with four states. Then the RSSI data acquired from two reader antennas and the information from a light barrier sensor are employed as features of a classification algorithm. The method is able to discriminate among static and moving tags and also to correctly assign a tagged item to the card box it belongs to. Besides the drawback of employing multiple antennas and an additional sensor, performance degrades when the distance among consecutive boxes is reduced. In this framework, in [4] a method has been proposed to employ the number of available readings and the time instants at which the tag passes in front of the reader antennas to determine the tag movement direction in an RFID gate system. It is worth mentioning other solutions employing the Doppler shift [5] or the standard deviation of the phase angle rotation [6] of the tag backscattered signal or a combination of both parameters [7], to discriminate among moving and static tags in indoor scenario with a relative motion among reader antenna and tags (e.g. mobile reader on a forklift).

The authors of this paper recently conceived a new phase-based localization technique for UHF RFID tagged items moving along a conveyor belt [8]-[11]. It is based on a synthetic-array approach that takes advantage of the fact that the tagged items move along a conveyor belt whose speed and path are known *a priori* (knowledge-based approach). The path can be of any shape and the instantaneous speed can be extracted from any control signal at the conveyor belt electrical engine, or measured through a simple kinetic sensor positioned along the belt border. In authors' opinion, the latter phase-based technique can be fruitfully employed, not only for tag localization and tracking, but also for discriminating among moving tags and other tags present in an indoor scenario, the latter being static tags or randomly moving tags. Besides, an accurate location estimation can be obtained for the moving tags. In Section II, the phase-based technique is briefly summarized. Then, classification results, when discriminating moving and static tags in a real scenario, are presented in Section III. Finally, conclusions are drawn in Section IV.

II. THE PHASE-BASED LOCALIZATION TECHNIQUE

A typical conveyor belt scenario is depicted in Fig. 1. Tagged items placed all around the indoor scenario could be detected from the reader antenna together with moving tags, and a discrimination among them is required.

Let us briefly summarize the method described in [8]-[11]. When a tag is moving along a conveyor belt, the phase variations of the reflected signal complex envelope (of a reading with respect to a reference one) are related to the variation of the relative distance between reader antenna and tag. A phase-variation history can be measured at the output of the reader I-Q receiver, and compared with nominal phase variations that can be easily constructed if the scenario geometry is known. Indeed, these latter can be analytically evaluated for a given assumed position of the tag on the conveyor at a reference time, if reader antenna position, belt path and belt speed are all known. Finally, a phase matching operator can be applied to determine the nominal history that best fits the measured phase variation history, resembling a (knowledge-based) synthetic array approach. The position associated to the so selected nominal history is chosen as the more likely position of the tag at the reference time. It is worth noting that, due to the anti-collision algorithms implemented in UHF RFID protocols and also considering that each backscattered signal contains the tag unique identifier, the parallel processing of multiple tags can be easily implemented, so allowing for a real-time localization. Furthermore, differently from other methods in the state-of-the-art, the proposed method can be implemented with only one reader antenna.

By considering a static tagged item placed close to the belt and detected during the same inventories of moving tagged items, a constant phase-variation history should be observed, since the reader antenna-tag distance does not change, and its recognition should be easily performed. However, due to several effects such as thermal noise, environmental clutter, multipath phenomena, interference from nearby tags, interference from people moving all around the scenario, such a constant curve could be deeply perturbed and its discrimination becomes more difficult. In this framework, the application of the above-mentioned localization algorithm, could be useful, as illustrated in the follow.

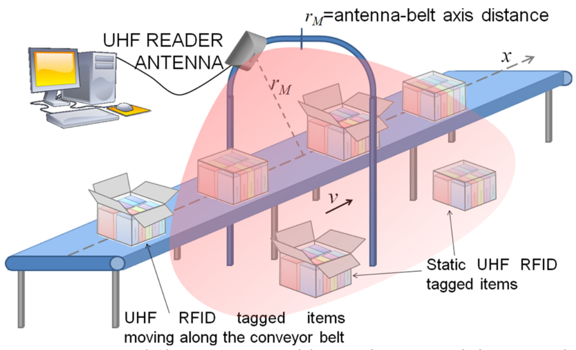

Fig. 1. Conveyor belt geometry with moving tagged items and static tagged items in an indoor scenario (v=belt speed, r_M=antenna-belt axis distance).

III. Classification Algorithm

The classification algorithm is here described and its effectiveness is demonstrated by using data acquired in a real indoor scenario, with reference to moving tags along a conveyor belt and static tags present all around the scenario.

A. Measurement setup

A measurement campaign has been carried out at the student restaurant of the University of Pisa, where a rectilinear conveyor belt is available for trays recovery. The measurement setup is shown in Fig. 2.

The commercial reader Intermec IF2 has been employed, which is able to measure the phase of the tag backscattered complex signal, with 1 degree precision on a 360 degrees range. The circularly polarized CAEN antenna WANTENNAX005, with $HPBW_H$=$HPBW_V$=67° and *Gain*=6.5 dBic, has been placed in front of the belt at a distance r_M=1.5 m. The reader output power, the working frequency and the interrogation repetition time have been set at P_{OUT}=24 dBm, f_0=866.2 MHz, and *IRT*=500 ms, respectively. Above mentioned geometrical and system parameters are employed in all the measured results shown throughout the paper. Preliminary measurements have been carried out by using one card box with 10 tagged items, which moves along the conveyor belt; another box has been placed besides to the belt (static box), still equipped with 10 tagged items. Alien ALN9640 Squiggle Inlay tags have been employed.

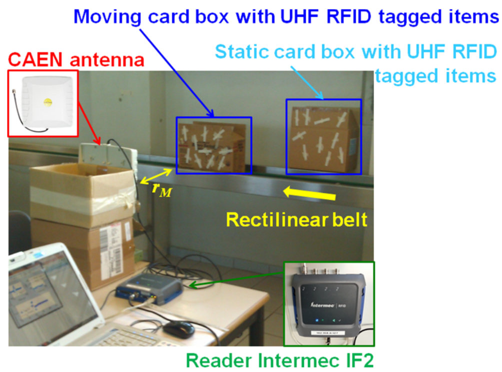

Fig. 2. Measurement setup to validate the new phase-based technique for discriminating moving and static tags in a rich multipath environment.

B. Algorithm features

As an example, measured phase-variation histories are plotted in Fig. 3, for a moving tag (circle markers) and for five static tags. For each tag, the phase curve is normalized with respect to the phase sample associated to the first available reading. N_r=33 readings are collected for the moving tag, while N_r={41, 15, 41, 39, 38} are collected for the other static tags, respectively, in a 20 s time interval. As expected, a quadratic-like phase behavior is observed for the moving tag. Above measurements also demonstrate that phase history can deviate significantly from a theoretical constant behavior, for static tags in a real indoor scenario. Indeed, phase deviations even larger than 70 degrees have been observed (mainly between 10 s and 20 s, which corresponds to the interval in which the moving box passes in front of the static box). However, the application of the above described phase-based localization technique [8]-[11] can face this problem as shown in the matching function illustrated in Fig. 4 (the latter being the localization algorithm output with respect to the hypothetical tag position, at the time of the last available reading). A well distinct peak appears by applying a global fitting of the phase-variations history of the moving tag (circle markers). On the contrary, a well distinct peak cannot be observed when processing the static tags phase history.

Consequently, the peak value of the above matching function can be employed as a first feature of a classification algorithm.

It is worth noting that for localization purposes, the peak position of the matching function represents the estimated tag position at an assumed reference time. By considering several tags on the moving box, the outputs have to be synchronized at the same reference time, and this can easily done by the knowledge of the belt path and speed. With reference to a single test case, the estimated tag positions for 10 moving tagged items are illustrated in Fig. 5, by considering a number of available reading N_r=9 for each tag. All tags are localized in a spatial interval of 44 cm. Since the box size is equal to 38 cm, an average error of the order of a few centimeter in the tag position accuracy can be assumed. This means that the algorithm outputs can also be used to correctly determine which box each tagged item lies in, if the boxes are a distance larger than 10-15 cm.

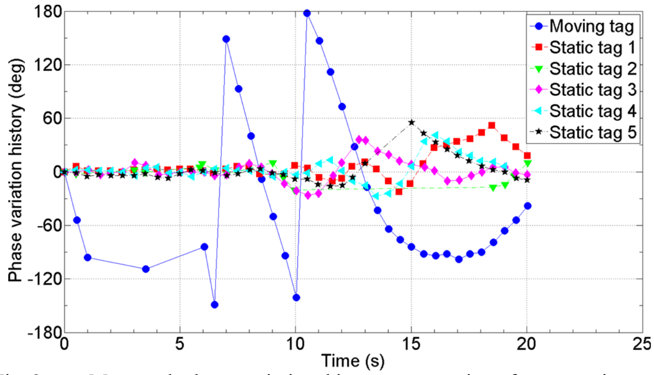

Fig. 3. Measured phase-variation history versus time for a moving tag along a rectilinear conveyor belt (circle markers) and for five static tags. N_r=33 readings are collected for the moving tag, while N_r={41, 15, 41, 39, 38} are collected for the other static tags, respectively.

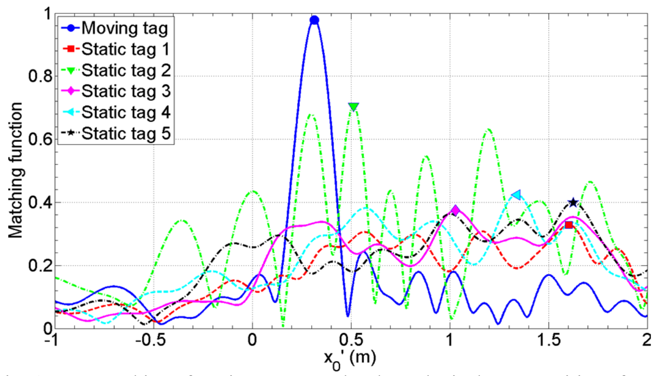

Fig. 4. Matching function versus the hypothetical tag position for a moving tag along a rectilinear conveyor belt (solid line) and for five static tags.

After collecting a minimum number of readings, the phase-based localization technique can be performed. Then, as soon as a new reading is available, the processing can be repeated by considering a minimum number of available readings $N_{r,min}$, with a moving window processing. The estimated tag position versus the time of the last reading is illustrated in Fig. 6 for the case of $N_{r,min}$=9. For the moving tag, such curve describes the trajectory of a uniform linear motion and its slope is expected to match with the belt speed (known *a priori*). The output of the phase-based localization processing (namely an estimated tag coordinate along the conveyor axis) is meaningless for a static tag, as its phase history is different from that expected for a tag moving along the conveyor. Indeed, for the static tag, the slope of the curve in Fig. 6 is quite different from that of a moving tag (estimated speed is much lower than actual belt speed). Consequently, the speed estimated from the slope of curve obtained by consecutive estimated tag positions (moving window processing) can represent a further feature of a classification algorithm.

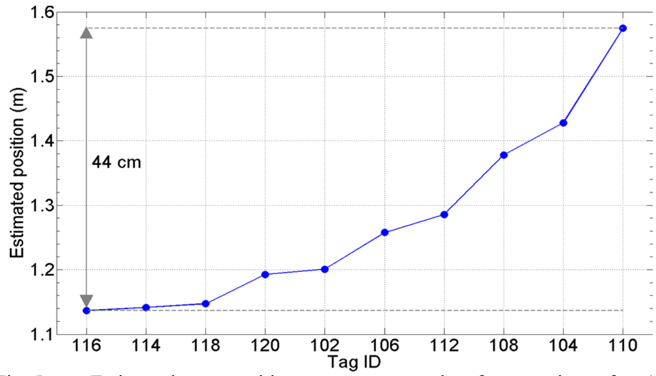

Fig. 5. Estimated tag position at an assumed reference time, for 10 moving tags in a card box (38 cm wide) moving along the conveyor belt; N_r=9 available readings for each tag.

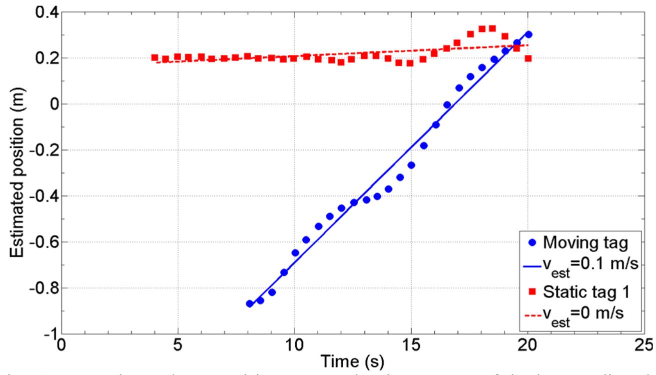

Fig. 6. Estimated tag position versus the time stamp of the last reading, by applying a moving window processing with $N_{r,min}$=9, for both a moving tag (circle markers) and a static tag (square markers).

C. *Discriminating moving tags and static tags*

A preliminary scatter plot analysis has been carried out to verify the effectiveness of the classification features got from the localization algorithm and illustrated in the previous paragraph. In the moving window processing, several matching functions are obtained, thus the average of all the peak values is considered as a first feature of the classification algorithm. Besides, the estimated speed extracted from the estimated tag position versus time (normalized with respect to the known belt speed) is also employed as a second algorithm feature. Thus, two parameters can be collected and their usefulness can be demonstrated through the scatter plot in Fig. 7. The latter has been obtained by considering a test case with 20 tagged items (10 tags inside the moving card box and 10 tags attached to the static card box). Two point clouds appear well separated and this suggests the possibility to fruitfully use the above parameters as input features of a classification algorithm.

To proof the idea, a standard *K-Means* classification algorithm has been employed [12]. Several test cases have been performed by varying the number of moving tags and static tags and results in terms of confusion matrix are shown in Table I, by considering a minimum number of readings in the moving window processing, $N_{r,min}$=9. Performance is almost independent from the number of detected tags and the classification accuracy is good even if few tags are detected. By considering average performance, the false positives (static tags classified as moving) percentage is 3.4%, while the false negatives (moving tags classified as static) is 1.3%. Besides, the percentage of the overall accuracy, namely the number of correctly classified tags with respect to the total number of tags is always greater than 93% for the various combinations of static and moving tags, with an average value of 95.3%. Confusion matrices have also been evaluated by varying the number of readings in the moving window processing in the interval $N_{r,min}$=[9, 13, 15, 17, 19]. 9 repeated test cases have been considered and results show that the overall accuracy is stable around 98% independently from the $N_{r,min}$ value, confirming the robustness of the chosen algorithm features.

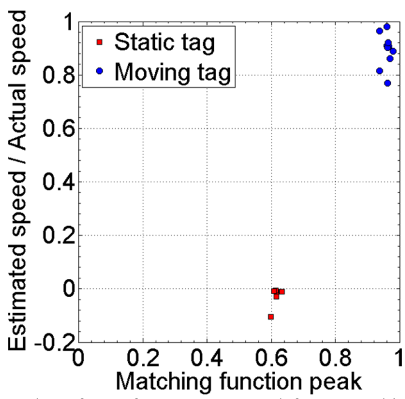

Fig. 7. Scatterplot of two features extracted from matching functions got for 10 moving tagged items (circle markers) and 10 static tagged items (square markers). A moving window processing with $N_{r,min}$=21 has been employed.

Table I. Confusion matrices as results of 10 repeated tests by performing a moving window processing with $N_{r,min}$=9 and various combinations of moving and static tags.

			5 moving tags		**10 moving tags**	
			Predicted class			
			Moving	*Static*	*Moving*	*Static*
1 static tag	*Actual class*	*Moving*	48	2	97	3
		Static	1	9	0	10
5 static tags		*Moving*	49	1	100	0
		Static	5	45	5	45
10 static tags		*Moving*	49	1	100	0
		Static	9	91	9	91

Obviously, the overall accuracy can be improved by implementing an advanced classification algorithm. However, the fact that a basic implementation of the *K-Means* method allows to get satisfactory results, confirms the method capability in discriminating moving and static tags.

IV. Conclusion

The application of a phase-based technique for discriminating moving and static tags is presented, with reference to a conveyor belt scenario. Thanks to the *a priori* knowledge of the conveyor belt path and speed, the tag backscattering signal phase behavior of moving tags can be recognized from that of other tags present in the indoor scenario.

In preliminary measurements, it has been shown that the proposed method is able to discriminate among moving and static tags with an overall accuracy greater than 96%, by using only one reader antenna. This is the main advantage with respect to other approaches that require at least two reader antennas. In future work, a different classification algorithm will be investigated, together with the potentials of other parameters got from the phase-based localization algorithm.

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