TRANSIENT ADAPTIVE POLARIZATION CONTRAST TECHNIQUES IN TIME-DOMAIN SCATTERING WITH APPLICATIONS IN THROUGH-WALL MICROWAVE IMAGING

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INTRODUCTION

The Adaptive Polarization-Difference Imaging (APDI) algorithm is a bio-inspired technique that is evolved as an adaptable, further expanded development of the well-proven PDI technique (see e.g., [1], [2]). Both methods were originally developed for optical imaging and in many situations can provide significant enhancements in target detection and feature extraction over conventional methods. Simulation and experimental results in the visible spectrum have confirmed that the APDI technique can, in certain situations, perform more effectively than the non-adaptive PDI techniques [4]. Our current goal is to transfer the adaptive technique developed for optical imaging to the transient time-domain microwave signals with particular applications in through-wall microwave imaging (TWMI). This work is a part of TWMI project currently running in our research group. One of the main challenges in a TWMI system is to discriminate between the targets and the clutter, and to locate both moving and/or stationary objects behind opaque obstacles such as a wall. In TWMI applications it is desirable to have a complete system with the ability to sense and identify objects behind various types of walls. The preliminary results of application of APDI for TWMI problems were presented in [5]. In this paper we study the use of transient adaptive polarization contrast schemes for target detection purposes.

DESCRIPTION OF TRANSIENT APDI ALGORITHM

In APDI, a statistical analysis of the polarization parameters of the scene (particularly when we encounter non-uniform probability density functions for polarization statistics) is performed, utilizing the well-known Principal Component Analysis (PCA) technique [6], and new adaptive signals are composed. These signals provide a better recognition of a target-object against the background. The target is defined as a region of the scene with distinctive polarization characteristics as compared to the background. These principal component (PC) signals are known to be optimal information channels for a given scene [3] and are composed as a linear combination (here with unequal weighting coefficients) of the two original polarization signal channels. In practice, we determine the optimal orientation of the polarization filters with weighted outputs such that the optimum target-to-background separation can be achieved. Several criteria can be utilized, such as maximum multiplicative coefficients, in the principal component outputs, and the maximum variances for the second and/or third principle components, in order to determine the optimal channels.

In this paper we describe only a portion of APDI algorithm which is related to the transient case. For a complete overview of the technique reader should refer to references [4] and [5]. In TAPDI we analyze the transient electromagnetic fields scattered from the observed scene during a certain temporal interval. As a result, we apply the APDI algorithm for the electromagnetic fields scattered from the scene in the time domain. Here we do not utilize phase information, and use only transient amplitudes of co- and cross- polarized components of the scattered field in the plane of the receiving antenna.

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Consider the scene of interest being illuminated by a temporally-modulated Gaussian signal with a –3dB frequency band being within the TWI system's frequency band of operation. For the sake of brevity we present here only the technique as it is applied to a case of incident field being polarized in the θ direction. The case of a φ-polarized incident field follows an identical procedure. We assume that the electromagnetic field scattered from the object (either a single object or a group of objects) is known and is given by the transient amplitudes of co- and cross- polarized components, i.e. E_θ, E_φ, at the observation plane during a given period of time. Here θ and φ are the elevation and azimuth angels in the spherical coordinate system. Therefore, at each temporal step t_n we have a pair of amplitudes at $m_1 \times m_2$ spatial points of the observation plane. Here, without loss of generality, we assume that $m_1 = m_2$.

The main assumption for the APDI algorithm is that the initial set of data must contain at least two sets of co- and cross- polarized components of the electromagnetic field (either measured or numerically simulated) scattered from the object. We assume that the first set of data corresponds to "background" (or "non-target") scene, and the second set is those for the "target" scene. These scenes, in general, may contain same objects. For TAPDI we need the abovementioned information within a certain interval of time. Hence, for each polarization of incident field initial data consists of the two sets of temporal distributions of $E_\theta(t_n)$ and $E_\varphi(t_n)$ at each spatial point in the plane of receiving antenna system.

TheTAPDI technique is then applied as follows. From the field scattered from the background scene for each temporal frame we create a set of pairs of signals, i.e. $E_n(\psi_1)$ and $E_n(\psi_2)$ as:

$$E_n(\psi) = E_\varphi \cos\psi + E_\theta \sin\psi \ , \tag{1}$$

where ψ is the angle of orientation of the polarization plane of receiving antenna, subscript n identifies the temporal frame where $n = 0$ corresponds to the moment when the transmitting antenna sends the pulse. It should be noted that all calculations given below occur at the each temporal frame t_n and the corresponding parameters are marked with subscript n. We assume that the angle ψ varies between 0 and 180 degrees with a step of $\Delta\psi$ degrees, so we have $(180/\Delta\psi)^2$ combinations of signals. Applying the Principal Component Analysis (PCA) algorithm to those pairs of signals, we get a set of all four adaptive parameters, i.e., eigenvalues λ_{1n}, λ_{2n} and coefficients α_n, β_n as functions of angles (ψ_1, ψ_2). As a next step, we found the optimal orientations of the receiving antennas, i.e. ψ_{1n}^{opt} and ψ_{2n}^{opt} with the corresponding optimal adaptive coefficients, i.e. $\alpha_n^{opt} = \alpha\left(\psi_{1n}^{opt}, \psi_{2n}^{opt}\right)$ and $\beta_n^{opt} = \beta\left(\psi_{1n}^{opt}, \psi_{2n}^{opt}\right)$.

Using the second temporal set of data, i.e. the "target scene", we construct the two output signals for the optimal pair of angles, i.e., ψ_{1n}^{opt}, ψ_{2n}^{opt}:

$$\begin{aligned} PC_1(t_n) &= -\beta_n^{opt}\tilde{E}_n(\psi_{1n}) + \alpha_n^{opt}\tilde{E}_n(\psi_{2n}), \\ PC_2(t_n) &= \alpha_n^{opt}\tilde{E}_n(\psi_{1n}) + \beta_n^{opt}\tilde{E}_n(\psi_{2n}), \end{aligned} \tag{2}$$

where PC_1 and PC_2 are the principal components of the scene at a given moment of time t_n, $\tilde{E}_n$ are the output signals from the two antennas, taken from the "target scene" data. It should be mentioned again that optimal adaptive coefficients were found solely based on the statistics of the "background" scene. Our conjecture is that by observing temporal variations of the principal component signals, we may detect presence of "target objects".

APPLICATION OF TAPDI TO TARGET DETECTION IN TWMI SCENARIO

To illustrate TAPDI algorithm we analyze the scene consisting of a large wooden plate 200 cm x 80 cm and several metallic cylinders located in front of the wall. The geometry of the problem and all dimensions of the objects are shown in Fig. 1. The objects in the scene are a wooden plate and several metallic cylinders in different combinations. To investigate the potential of the proposed algorithm in detecting changes in orientation of a single cylinder and appearance of the additional cylinder in the scene we consider here two examples. As the first example we consider the cylinder #1 (see Fig. 1) as the background (to be referred as case A) and the cylinders # 2 (Case B) and #3 (case C) as the two target scenes. The objective in this case was to distinguish between shift and tilt of the cylinder. In the second example we have a metallic cylinder #3 as the background scene with the cylinders #2 and #4 added, one at a time, to the scene as targets. The goal was to detect additional cylinder and distinguish between their changes in location. For both examples we first calculated PCs of the background scene based on its own statistics and then using the statistics of the background scene obtained PCs for the target scenes. The incident field was the Gaussian beam with its maximum at 2.5 GHz and had –3dB points (with respect to maximum) at 2 and 3 GHz. The frequency range of the beam coincides with the operation band of the TWMI system under development [5]. The incident direction was at $\theta = 90^\circ$, $\varphi = 90^\circ$. The dielectric constant and loss tangent of the wood were assumed to be $\varepsilon = 7$ and $\tan\delta = 0.0194$, respectively. In our study, the scattered field was calculated using the FDTD-based commercial software package XFDTD® from REMCOM, while in the real TWMI system the scattered field will be obtained through measurements. The simulations were performed on a Dell™ Precision 670 workstation with 2.8 GHz Intel Xeon dual CPU and 4 GB of RAM.

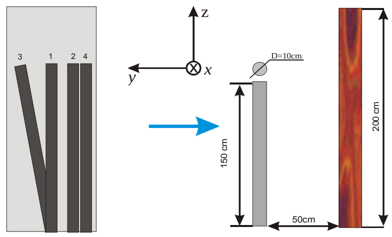

Fig. 1. Geometry of the problem. The direction of incident wave propagation is indicated by the blue arrow

The scattered field was computed for $n = 2000$ temporal steps, and the total temporal interval was $t = 19.26\,ns$ for both scenes (i.e. background and target). The observation plane of the antenna was given by angular variation of both θ and φ from 85 to 95 degrees. Hence for each temporal step we had 121 spatial points in which E_θ and E_φ were known for both "background" and "target" scenes within given temporal intervals. This information enabled us to simulate pairs of signals for any combinations of ψ_{1n} and ψ_{2n} according to (1). Applying the PCA technique to all those signals, we obtained optimal set of adaptive coefficients at each temporal step. As was previously shown in [5], the optimal parameters are found to be corresponding to the maximum value of coefficients α_n and β_n. Finally, the principal components of the scene were obtained using (2). It should be mentioned that the same procedure was used for both polarizations of the incident field. As a result of the simulations, temporal distributions of both PCs for both polarizations of the incident field were obtained.

Due to the format of the paper we cannot present temporal dynamic changes in PCs as a movie clip. Instead we show the variation in time of the average value of corresponding component. For the sake of brevity, we give here only results corresponding to θ-polarized incident wave. In Fig. 2 the temporal variations of mean values of PC_1 and PC_2 in each frame are presented. Panels *a*) and *b*) of Fig. 2 show PC_1 and PC_2, respectively, for all temporal intervals in example #1. One may notice that mean values of PC_1 behave very similarly for cases A–C, while mean values of PC_2 for cases B and C, although of similar shape, have almost ten times difference in amplitude. In panel b) we show those curves in the same plot with different scales for left and right hand side ordinates. This means that our technique was under this condition capable of distinguishing between shift and tilt of the cylinder. In the second example target cylinders in cases E and F were very close to each other which represented a particular challenge in detecting their position. The results are shown in panels c) and d) of Fig. 2 for mean values of PC_1 and PC_2 in the each temporal frame, respectively. Observing temporal distribution of PC_2 one may observe a certain distinction between cases E and F, which shows that the proposed technique was also able to distinguish between those two cases.

CONCLUSIONS

In this paper we proposed transient APDI as a new potential technique for target detection and discremination, and presented preliminary results on its applications to the TWMI problems. The proposed technique enables one not only to detect the targets but also distinguish changes in their locations. Although the test cases studied were rather simple, the TAPDI showed that it has potential of being successfully implemented in a TWMI system.

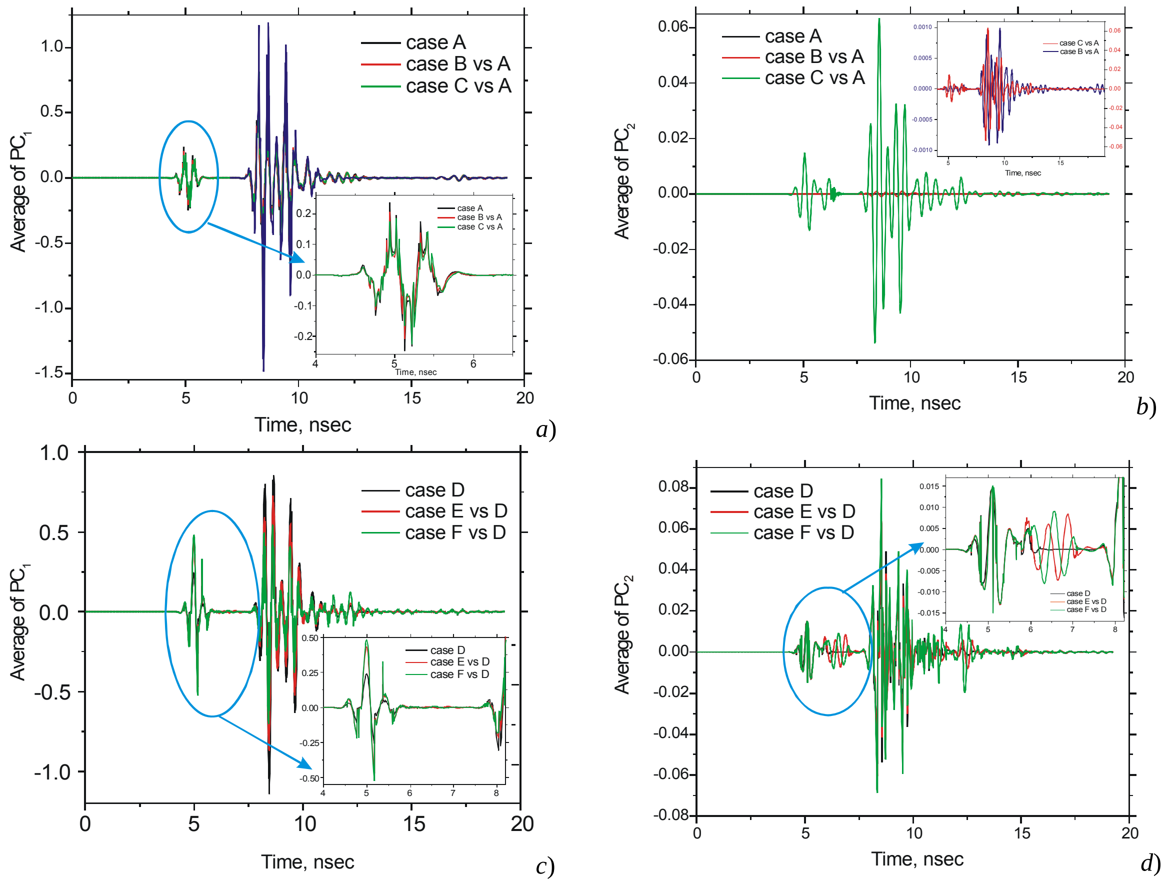

Fig. 2. Temporal variations of mean values of corresponding PCs. Case A – PCs for cylinder #1 based on its own statistics, case B – cylinder #1 was the background and cylinder #2 was the target, case C – cylinder #1 was the background and cylinder #3 was the target. Case D – PCs for cylinder #3 based on its own statistics, case E – cylinder #3 was the background and cylinders #3 and #4 were targets, case F – cylinder # 3 was the background and cylinders #3 and # 2 were targets

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