Application of Particle Swarm Optimization in Linear Constraint Minimum Variance Beamforming Technique

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Abstract: Smart antenna that transmits and receives the signal as the beam form is a part of cellular system in wireless communication. One of the beamforming techniques that employ in smart antenna is the Linear Constraint Minimum Variance (LCMV) beamforming. The LCMV beamforming technique forms its radiation beam towards desired signal through its weight vector which is computed through received signal. However, weights computed by LCMV usually are not able to form the radiation beam towards the target user precisely. Hence, LCMV technique must be improved to support the system with higher quality. To solve this problem, in this paper Particle Swarm Optimization (PSO) is incorporated into the existing LCMV technique in order to improve the weights of LCMV, Signal to Interference Noise Ratio (SINR), throughput of system and data rate. This study presents the results from analysis of the designed model and general characteristic of that and presents a graphic analysis used to evaluate the appropriateness of the model parameters and the overall goodness-of-fit of the model. The obtained results in this study, which is the optimized output of LCMV beamforming, are simulation by comparing the output results in different scenarios.

Key words: Smart antenna, Adaptive Beamforming, Linear Constraint Minimum Variance (LCMV), Particle Swarm Optimization (PSO).

INTRODUCTION

Nowadays, wireless communication system plays a significant role in people’s life. According to the observation, there is an increasing demand for mobile communication service. The unstable rate of rising of demand provides an expectation of active wireless device everywhere at every time in the near future in the world. Therefore, the growing of the requirement is cause of the escalating the array of antenna on satellite, vehicle and base station (Karakayali et al. 2006, Foschini et al. 2006, Choi & Andrews 2007). Additionally, mounting array of antenna is cause of rising demand for more channels with larger bandwidth and low price (Lal C. Godara 1997). This demand can become a fact for more channels only by reducing the bandwidth of radio frequency. Base on this problem there is a need of new technology known as smart antenna (Salvatore et al. 2002, Balanis 2003), with using the beamforming method which can solve the limitation of bandwidth (Balasem et al. 2010, Susmita 2009). Adaptive antenna (Compton 2011, Balasem et al. 2012) which transmits and receives the signal as the beam form is the significant part of cellular system in mobile communication classification that has substantial effect on GSM and CDMA system (Liu 2007). Beamforming technique that is completed by signal processing method, adjust direction of transmitted or received signals in order to making the beam pattern toward the desired direction (Ma 1974, Dahrouj & Yu 2010, Rana et al. 2011). Consequently, in support of this object, beamforming technique attempts to enhance sensitivity in desired direction and reduces the sense in undesired direction by calculating the Direction of Arrival (DOA).

One of the beamforming techniques that is used in smart antenna is the LCMV beamforming (Tseng & Griffiths 1992, Frost 1972, Booker et al. 1969). This technique has a great influence on increasing the capacity, better data rate and coverage (Mehrez et al. 2010) and it is stronger and tougher in noisy environment to compare with other techniques of beamforming. Hence there are a large number of advantages for LCMV beamforming technique while the disadvantage is computed weight. The weights of LCMV technique are usually not good sufficient for taking expected performance of the system. These weights must show an acceptable design of the beam pattern in target of user. It is difficult to improve and optimize the LCMV beamforming technique through conventional empirical approach. Hence, artificial intelligent (AI) technique is explored to enhance the LCMV beam forming ability.

There are various AI techniques that a large number of these are inspired by animal behaviors and their environment. According to the previous researchers, one of the best optimization techniques based on population search is the PSO technique (Kennedy & Eberhart 1995, Heppener & Grenander 1990, Reynolds 1987, Eberhart & Shi 2001, Darzi et al. 2013a). The current paper presents the optimization of LCMV weights by the PSO technique in order to improve the performance of the system.
Particle Swarm Optimization (PSO):
This paper tries to explain how the PSO method will be carried out to optimize the LCMV beamformer output. In order to do this, in the first step, four weights of LCMV are calculated and they use as input for PSO technique. Based on Figure 1, which is the output of LCMV beamforming technique, the target of desired signal is assumed at 45 degree and interference is at 30 and 50 degree. The purpose of this study is to optimize of LCMV weights for have better throughput in system. Hence, increases the power of target at 45 degree and decrease the power of interference in 30°, 50° are aim of this study.

Fig. 1: LCMV Radiation Beam Power Response.

Base on the calculation of 4 complex fractional weights of LCMV, in this part the estimated weights will be optimizing by PSO technique. In PSO method, need to produce population at first. The input that is obtained from output of LCMV is complex number. It means the population also must be complex value. The population value is random and is depend on boundary in PSO.

PSO method has upper bound and lower bound and putting the true value for them is very important and has a huge effect on operation of PSO because velocity and position of each particle is depending on that. If the upper bound and lower bound be the small value, it means the rate of movement for particles is low and need long time to move. But the particles cannot search in extended area and chose best place because area is small and program very soon stops. While if the upper bound and lower bound be big value, the rate of movement of particles is very fast. But they should search in big area for chose best place that need long time. In fact the boundary value must not be too small or too big and depends on input.

The population and velocity are produced depend on upper and lower bound. In the next step, the fitness value is calculated for each population and put the maximum one in the memory. Later, the population and velocity are updated based on the best fitness value in order to gather the particles to the desired direction. Currently, the fitness value is calculated for new population to choose the maximum fitness value and compare with the previous maximum one. If the current value is more than the previous one, the new value will be replaced to the old one. While if obtained value is less than the previous one the old value will be remain in the memory. This procedure will be continued till the defined number of iteration finished.

Figure 2 demonstrate various steps of optimization of LCMV beamforming technique that take place in this study.

Simulation and Result of LCMV Optimization:
In this part the optimized output of LCMV is simulate by comparing the result of optimization in different boundary and iteration conditions. Base on these circumstances, While PSO can optimize the output of LCMV in each situation; the optimization result is depending on some conditions such as upper bound, lower bound and number of iteration which can be change. In addition, the significant case in this study is producing random population and velocity that is changing by varies of iteration and boundary value which is cause of changing the result in different scenarios. Hence, Base on changing the boundary and iteration value in different situation, the SINR value will be change.

Comparing the Result of LCMV Optimization in Different Boundary:
Boundary in PSO technique has a different range of angle and amplitude because it is defined as a fractional number in this study. Here the change of amplitude and angle in upper and lower bound are utilized to check the
effects the value of boundary in optimized output results. Table 1 illustrates the various output of PSO technique by using different boundary.

**Fig. 2:** Proposed Algorithm for optimization of LCMV using PSO.

**Fig. 3:** SINR Improvement in Different Boundary Values and Constant Iteration.
Table 1: PSO Output in Different Boundary.

<table>
<thead>
<tr>
<th>Number of Boundary</th>
<th>Value of Boundary</th>
<th>SINR</th>
</tr>
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<tbody>
<tr>
<td>Boundary 2</td>
<td>Lower Bound= [-7.7153-5.5784i, -7.8706-6.1641i, -8.1008-6.0819i, -8.0086-5.6789i]; Upper Bound= [7.7153+5.5784i, 7.3706+6.1641i, 8.1008+6.0819i, 8.0086+5.6789i];</td>
<td>1.1003</td>
</tr>
<tr>
<td>Boundary 3</td>
<td>Lower Bound= [-5.8153-3.3784i, -5.0706-3.6641i, -5.7008-3.6819i, -5.3086-3.6789i]; Upper Bound= [5.1153+3.2784i, 5.1706+3.6041i, 5.1008+3.1819i, 5.1086+3.1789i];</td>
<td>1.1610</td>
</tr>
<tr>
<td>Boundary 4</td>
<td>Lower Bound= [-4.9153-2.2724i, -4.9106-2.0641i, -4.9008-2.0819i, -4.9086-2.2729i]; Upper Bound= [4.9153+2.2724i, 4.9106+2.0641i, 4.9008+2.0819i, 4.9086+2.2729i];</td>
<td>1.4088</td>
</tr>
<tr>
<td>Boundary 5</td>
<td>Lower Bound= [-2.3153-1.2724i, -2.6106-1.0641i, -2.6008-3.0819i, -2.3086-3.2729i]; Upper Bound= [2.3153+1.2724i, 2.6106+1.0641i, 2.6008+3.0819i, 2.3086+3.2729i];</td>
<td>1.5772</td>
</tr>
<tr>
<td>Boundary 6</td>
<td>Lower Bound= [-1.8153-0.3784i, -1.0706-0.6641i, -1.7006-0.6819i, -1.7086-0.6789i]; Upper Bound= [2.1153+1.2784i, 3.1706+1.0641i, 3.1086+1.1819i, 3.1086+1.1789i];</td>
<td>2.3870</td>
</tr>
<tr>
<td>Boundary 7</td>
<td>Lower Bound= [-1.3153-1.2724i, -1.6106-1.0641i, -1.6008-1.0819i, -1.3086-1.2729i]; Upper Bound= [1.3153+1.2724i, 1.6106+1.0641i, 1.6008+1.0819i, 1.3086+1.2729i];</td>
<td>1.7899</td>
</tr>
<tr>
<td>Boundary 8</td>
<td>Lower Bound= [-0.8153-0.5724i, -0.8106-0.4641i, -0.7008-0.4819i, -0.5086-0.4729i]; Upper Bound= [0.8153+0.5724i, 0.8106+0.4641i, 0.7008+0.4819i, 0.5086+0.4729i];</td>
<td>0.8799</td>
</tr>
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</table>

As observed in Figure 3, with decreasing of boundary values from high value to small one, the algorithm shows a significant increase in SINR value. The SINR value increases from 0.8 to 3.4 in different boundaries from high to small bound according to Table 2. This Figure shows the obtained SINR in different level of boundary when the iteration number is constant. SINR changes from 0.8 to 1.097 in boundary1 when iteration number is 50. This value starts from 0.8 due to original SINR value in LCMV beamforming. SINR number changes from 1.1003 to 1.1462 in boundary2 and 1.1610 to 1.3635 in boundary3 when the iteration number is 50. In the same iteration, the SINR value changes from 1.4088 to 1.4291 in boundary4 and from 1.5772 to 1.7484 in boundary5. In boundary 6 the SINR shows the best result from 2.0761 to 3.4038. Besides boundary 7 and 8 show the decreasing boundary that has an effect on decreasing SINR. It means, that the SINR increase with decreasing the amount of boundary value until boundary 6, meanwhile more decreasing of the boundary value is the cause of reducing of the output. Base on the output results the boundary value cannot be very small because the particles cannot find best position in very small space. The bound value has a significant effect on result of SINR because it limits the search space for particles.

One of the reasons for different results of SINR in different boundary is the constant iteration due to the requirement of large search space with more iteration number in compare to small search space. Hence in global search, particles need more time to try for finding the objective place in compare to local search.

Comparing the Result of LCMV Optimization in Different Iteration:

In this part changing the iteration number is employed to check the effects of number of iteration in optimized output results. Figure 4 illustrates the optimization output of LCMV by PSO in different iteration while the value of boundary is constant in each scenario. The boundary 6 is considered as a value for boundary as shown in Table 1.

In Figure 4, it is observed that with the increasing the number of iteration, the algorithm shows improvement of throughput. Throughput of SINR increases from 0.8 to 3.4 when the number of iteration increases from 1 to 50 in constant bound value. In this study the iteration of 50 brings greater possibility of higher SINR while this value stays constant with increase the number of iteration. Thus SINR has a significant change from 0.8 to 3.4 among iteration of 1 to 50 while 50 is last step of increasing SINR.
Fig. 4: SINR Improvement in Different Iteration Value and Constant Bound Value.

**Conclusion:**

Today, building an acceptable beam pattern in smart antenna is one of the most concerns of wireless communication system. While many methods try to build the beam pattern, there is no study on employing PSO method to optimize the built beam pattern by LCMV technique. Consequently, the present study is used to improve the output of LCMV by putting them as input of PSO and producing random population and velocity based on that. Base on the output of the study, the optimization LCMV by PSO reveals the high $\text{SINR}$ value that is the high level of acceptance and accuracy. Furthermore, this paper simulates the optimized output of LCMV by comparing the result of optimization in different iteration number and boundary conditions. In the first step the boundary assumed with eight values for lower and upper bound when the number of iteration is constant. The resulted output reveals that decreasing the boundary value till the certain limitation has a significant effect on improving the $\text{SINR}$. In the next part, there is simulation for LCMV output in different number of iteration. Result of $\text{SINR}$ increases from original value to maximum result when the number of iteration increases from 1 to 50 in constant bound value.

**REFERENCES**


