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Research Article

Indoor Pedestrian Positioning Tracking Algorithm with Sparse Anchor Nodes

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In order to solve the indoor pedestrian positioning and tracking problems under the condition of sparse anchor nodes, this paper presents a new tracking scheme which predicts the staff position under the condition of indoor location fingerprints based on particle filter. In the proposed algorithm, the indoor topology is adopted to constrain and correct the results. Simulation results show that the proposed algorithm can significantly improve the accuracy of indoor pedestrian positioning and tracking more than the Kalman filter and k-nearest neighbor (KNN) algorithms. The simulation results also show that under the condition of sparse nodes deployment good tracking results can still be achieved through the adoption of indoor topology and the average positioning error is about 1.9 m.

1. Introduction

With the improvement of communication technology, location-based service (LBS) [1] has drawn more and more attention and will have a significant impact on human life and work. For example, the use of Global Positioning System (GPS) and electronic map in vehicle navigation and the use of intelligent mobile phone help people outside to find their place and route. Using a variety of sensors in indoor environments, for example, in a large supermarket or an exhibition hall can lead people to the places where they want to go. Although GPS can basically meet the requirements in outdoor environment for locating and tracking, it cannot work well in indoor environment. Currently the common adopted indoor localization techniques are mainly infrared, ultrasonic, ZIGBEE, wireless local area network (WLAN), ultrawide bandwidth (UWB), radio-frequency identification devices (RFID), magnetic signal, visual analysis and inertial measurement unit (IMU) [2], or the combination of multiple techniques.

Existing localization algorithms can be divided into the following three categories: range based, range-free, and event driven. Algorithms based on distance measurement need at least three sensors to locate trilateral using triangulation algorithm. Range-free algorithms are based on network connectivity information, which has lower location accuracy than the range-based algorithms. Event-driven localization makes use of localization events which are generated and propagated across the area where sensor networks are deployed. Although these algorithms are very effective, it is hard to employ them directly for the indoor positioning.

Indoor positioning and tracking order that sensors for locating should be deployed first. Increasing the density of coverage would increase the cost. In practice, the aim that the whole indoor area is covered by all anchors is often hard to achieve. Some dead angle inevitably exists. Considering the complexity of the indoor environment, the obstacle diffraction and reflection of the signal and the change of interior structure all have effects on the wireless signal for localization. Indoor localization and tracking should not only consider the normal usage, but also should consider the special cases, for example, the cases of fire or earthquake damage. Some anchor nodes or the order of the deployment of at least three sensors cannot be met [3]. In this paper, we put forward a positioning and tracking algorithm under the condition of sparse anchor nodes deployment, where the particle filter (PF) method based on the position fingerprint

is used and the constraints of the results of indoor topology and correction algorithms are also explored.

The rest of the paper is organized as follows. Section 2 briefly surveys previous localization methods. Section 3 presents the system overview and details the system design. Section 4 illustrates simulation results. Finally, Section 5 concludes the whole paper.

2. Related Work

Many excellent schemes have been proposed for the indoor localization. Most of them can be categorized into three classes: range-based localization, range-free localization, and event-driven localization.

Range-based localization algorithms are built on top of distance or angle measurements among the nodes in the networks, which require expensive hardware devices to estimate the distance between the nodes or need careful environment profiling. The Time of Arrival [4] and Time Difference of Arrival [5] schemes measure the propagation time of the signal and estimate the distance based on the propagation speed. The Angle of Arrival (AOA) schemes [6] estimate the node locations by sensing the received signal direction. The Received Signal Strength Indicator (RSSI) schemes [7] use either theoretical or empirical models to estimate the distance based on the loss of power during signal propagation. The fingerprint localization algorithm is based on signal strength, and it is with the benefit of simple calculation and high precision. The fingerprint based localization algorithm can be divided into two stages: the offline stage and the online stage [8].

To address the limitations of the range-based schemes, range-free localization schemes have been proposed, which attempt to locate sensors without costly ranging devices. The location of each node is estimated based on the knowledge of proximity to the anchor nodes. There are two kinds of localization schemes: anchor-based scheme and anchor-free distrusted localization scheme. Generally, range-free localization methods normally have low accuracy, highly depending on the density and distribution of the anchor nodes.

Recently, event-driven localization schemes have been proposed to simplify the node functionality and to provide high-quality localization. The key idea of these schemes is to use artificial events for localization. Although their effective range can reach hundreds of meters, it needs additional event generation devices and manual operations to generate artificial events.

In the tracking field, the location is often achieved through estimation and filtering like particle filters. It is a kind of method where Monte Carlo simulation is used to solve nonlinear and non-Gaussian problems of the Bayesian estimation [9]. It first uses a lot of weighted particles to represent the posterior distribution of the estimation. Then, particles are forecasted by transcendental motion equation information. Through the observed information, the weights could be updated accordingly. At last, the aforementioned two steps are run in cycles to realize the estimator of the distribution of the tracking.

3. Positioning and Tracking Algorithm under Sparse Anchor Nodes

In indoor wireless environments, various obstacles cause wireless signals irregular reflection and scattering. In addition, barrier properties such as metal, building materials, or human bodies could have different impacts on the propagation of wireless signals so that wireless signals in different buildings will have big gaps. Generally, positioning in indoor places requires the signals received from at least three anchor nodes, and receiving the signals from five or more anchor nodes can result in more accurate location (employing more than five or six nodes cannot further improve the positioning accuracy). Due to the specialty of indoor environments, wireless anchor node's deployment is hard to cover with at least three anchor nodes in every place. If the number is less than three, signals would be weak or the damaged results cannot provide the anchor nodes with any usable information for positioning, hence, causing intermittent positioning failure.

3.1. Tracking Algorithm. First, according to the principle of RSSI ranging, we set up the offline indoor radio frequency maps. Each point's signal strength is the average of several measurements, and the signal data format is $(x, y, \mathrm{RSS}_1, \ldots, \mathrm{RSS}_i, \ldots, \mathrm{RSS}_m)$, where x and y are coordinates and RSS_i is the detected signal strength of anchor node i. We calibrate the signal intensity maps and store them in the database. At the online stage, the moving target node receives the real-time RSS signal $(S_1, S_2, \ldots S_m)$. One should select the minimum Euclidean distance of the k results and look for the average location. As the observed value of the particle filter, one should also use the particle filter algorithm to get the final localization results. The formula of Euclidean distance between the received signal strength and the locating fingerprint can be expressed as follows:

$$d_i = \sqrt{\sum_{i=1}^{m} \left(\mathrm{RSS}_i - S_i\right)^2}. \tag{1}$$

According to the number of anchor nodes in positioning and tracking environments, indoor location tracking process should be discussed for the following two different situations: (1) the situation for sufficient anchor node's indoor positioning and (2) the situation for sparse anchor node's indoor positioning. In the first case, the target node is covered by three or more anchor nodes with the initial location being obtained by the KNN algorithm. Then, one can use particle filter to determine the final location. In the second case, the target node is covered by two, one or zero anchor nodes (note that the case of three collinear anchor nodes is similar to that of two anchor nodes). In this case, the location of the target node cannot be directly located, which will cause intermittent positioning failures. As shown in [10], the environments covered by two anchor nodes can locate two target locations which connect symmetrically with the two anchor nodes. When only covered by one anchor node, the range of the target node location is a circle with its radius the distance

from the anchor node, and zero anchor node coverage cannot be located [11].

Although sparse anchor nodes cannot directly locate the target nodes, some facts can be used for the positioning constraint. By setting the target node S's maximum speed as $v_{\max}$ m/s sampling time interval T, the anchor node coverage is r, and we can get the following constraint conditions.

(1) Set P_t as the current time's position, P_{t-1} for the location of previous time; there is $P_t < P_{t-1} + T * v_{\max}$; namely, the current moment's location is always in the scope of a circle whose radius is $T * v_{\max}$.

(2) If the target only receives the signals from two anchor nodes a and b, it means that the target cannot be covered by other anchors except a and b. We define the formula $x \in y$, which means that x node is within the communication range of y node. Then, the above situation can be expressed as $S \notin \{U - \{a, b\}\}$, where S is the target node and U is the collection of all anchor nodes in the network. By the same token, the target node is covered by one anchor node a, having the constraint $S \notin \{U - a\}$.

(3) If the target is not covered by any anchor, then we have $S \notin U$. In this situation, we will combine the following conditions to determine the target location as follows: the location at the last step, the maximum target speed limitation, and the area which cannot be covered by any anchor in the fingerprint database.

The aforementioned are the filtering conditions in the tracking process based on particle filter algorithm. If the particle cannot satisfy the above conditions, it should be filtered.

3.2. Particle Filter Process. For simplicity, the particle filter method refers to finding a random sample of groups in the state space transmission and, thereafter, to approximating the probability density function, where integral operation is replaced by a sample mean, and, hence, it achieves the minimum variance distribution process. The samples here refer to particles, while the number of samples $N- >\propto$ can approximate any probability density distribution. The detailed particle filter algorithm [9, 12] is given as follows.

(1) Initialization, sampling from the initial distribution of the particle:

$$x_0^i \sim p(x_0), \quad i = 1, 2, 3, \ldots, n, \tag{2}$$

where x_0^i is the ith sampling particle, $p(x_0)$ is the initial distribution of the ith particle, $\omega_0^i = 1/n$ is ith particle's weight, and n is total number of the particles.

(2) Weight calculation is as follows:

$$x_k^i \sim q\left(x_k \mid x_{0:k-1}^i, z_{0:k}\right), \quad i = 1, 2, \ldots, n. \tag{3}$$

The importance weights are calculated as follows:

$$\omega_k^i = \omega_{k-1}^i \frac{p\left(z_k \mid x_k^i\right) p\left(x_k^i \mid x_{k-1}^i\right)}{q\left(x_k^i \mid x_{0:k-1}^i, z_{0:k}\right)}, \quad i = 1, 2, \ldots, n. \tag{4}$$

And, the importance weights are normalized as

$$\overline{\omega}_k^i = \frac{\omega_k^i}{\sum_{i=1}^N \omega_k^i}. \tag{5}$$

(3) Resample x_k^i, $i = 1, 2, 3, \ldots, n$.

According to the importance weights $\overline{\widetilde{\omega}}_k^i$, resample is carried out to get the updated n particles, x_0^i, $i = 1, 2, \ldots, n$. And the redistribution of the particle weight $\omega_k^i = \overline{\widetilde{\omega}}_k^i = 1/n$.

(4) Output

state estimation:

$$\overline{\widetilde{x}}_k = \sum_{i=1}^N \omega_k^i \overline{\widetilde{x}}_k^i, \tag{6}$$

variance estimation:

$$P_k = \sum_{i=1}^N \omega_k^i \left(\overline{\widetilde{x}}_k^i - \widehat{x}_k\right)\left(\overline{\widetilde{x}}_k^i - \widehat{x}_k\right)^T. \tag{7}$$

Step (1) is performed only at the beginning of the algorithm, and the other steps are performed sequentially. Finally, the particle set $\{x_k^i, \omega_k^i \mid i = 1, 2, \ldots, n\}$ is updated to achieve the target posterior distribution tracking.

3.3. Indoor Topology Constraint. Many logic errors may occur in indoor locating cases, for example, positioning tracking information, jumping from one room to another room or to the corridor. In the process of fingerprint-based positioning, there may be a new position for penetrating a wall. Although the derived results are the optimum of the position, the actual route may be very long [13], which is much farther than the value of $T * v_{\max}$. In order to reduce these logic errors, we introduce indoor topology constraints into the positioning tracking algorithm.

Indoor topology structure can be described as a connected graph, and the distance between the two fingerprints can be obtained by using the Dijkstra algorithm and getting the monophyletic shortest path. The fingerprint of each adjacent position is taken as a node of graph where the connection line for the edge and the weights of edge represent the distance of position fingerprint.

In Figure 1(a), the gray box is the position fingerprint, and each box A, B, C, and D can be regarded as connected graph vertex, in which the adjacent points can be connected, as shown in Figure 1(b). Adjacent position fingerprint distance is set to 1, the available distance is 3 between A and B, and the distance from A to D though is 1, but actually the shortest path is 7. So, the indoor topology for positioning in the process of the shortest path can effectively filter out positioning location which is not in conformity with the conditions. As shown in Figure 2, P_{t-1} is the location a moment before; $P_{t'}$ is the location got from the KNN algorithm; R is the largest distance of target node; and $R = T * v_{\max}$. The two position's

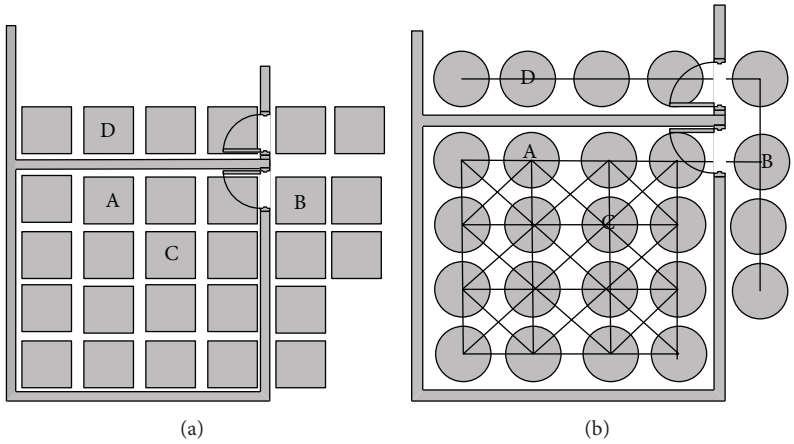

Figure 1: Position fingerprint diagram and connected graph example.

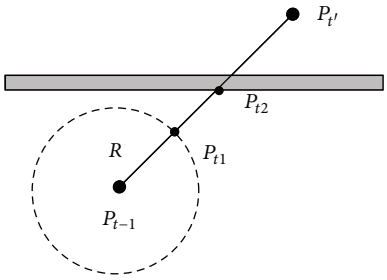

Figure 2: The confirmed location of the interior topology constraints.

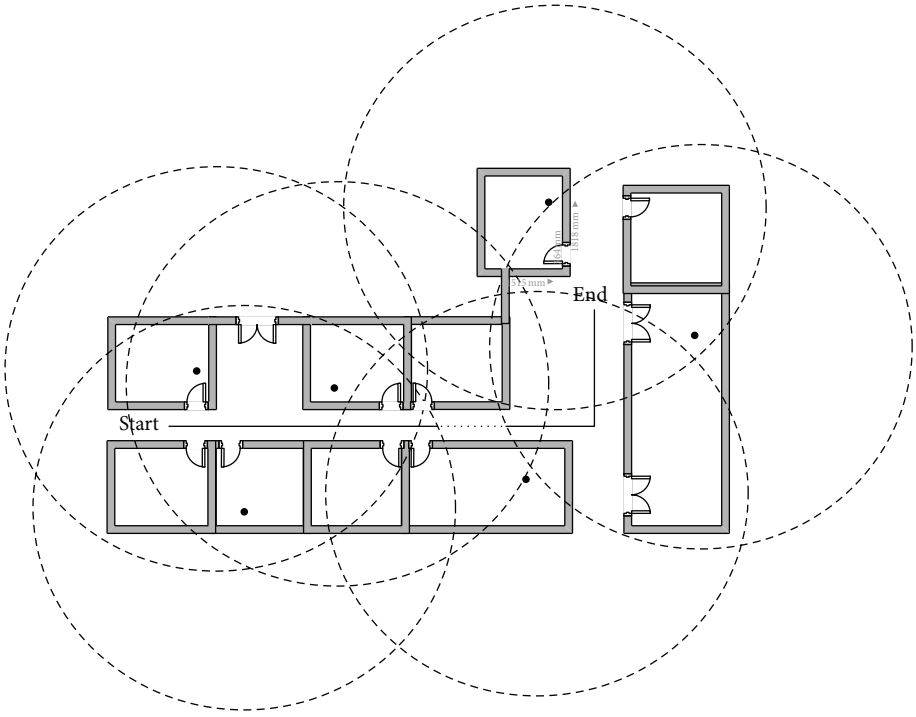

Figure 3: Simulation environment (• is an AP node).

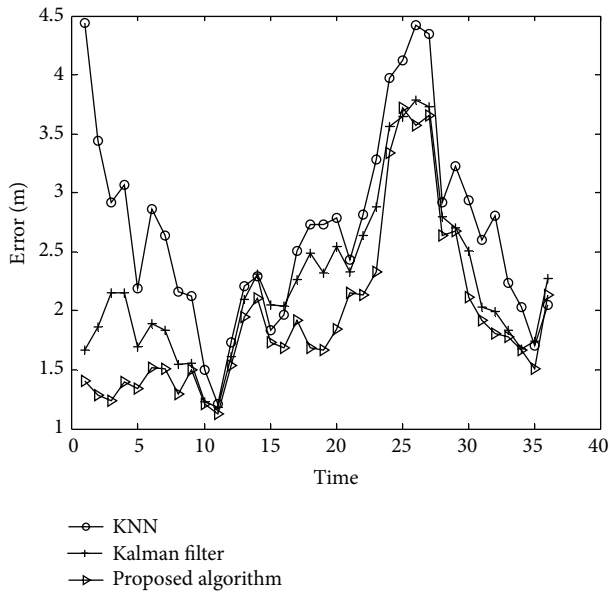

Figure 4: Accuracy comparison.

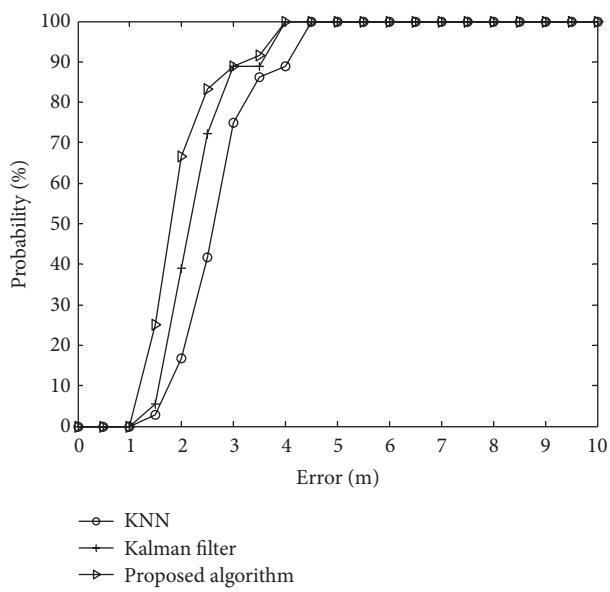

Figure 5: Accuracy comparison.

connections intersect the target node, respectively, and the target node moves along the circle and walls between P_{t1} and P_{t2}. The current position of P_t can be determined by

$$P_t = \begin{cases} P_{t1}, & (P_{t-1} + T * v_{\max} < P_{t2}) \\ P_{t2}, & (P_{t-1} + T * v_{\max} > P_{t2}). \end{cases} \quad (8)$$

So, the indoor topological constraints remove the location which mismatches the conditions, and it also identifies the location most close to the real location of P_t.

The indoor topological structure is basically the same. So, in the offline phase of the fingerprint procedure, one can calculate the shortest distance between two fingerprints' position and store the results in the database. Thereafter, one can get the new location from the database by using the particle filter under the indoor topology constraints and can get a more accurate estimated position.

3.4. Algorithm Flow. Algorithm 1 depicts the whole working flow. This is suitable for positioning and tracking under the sparse anchor node condition. Note that the algorithm is featured with the condition of small number of anchor nodes less than three which would lead to intermittent positioning failure.

Table 1: Tracking results comparison.

Algorithm	Percentage in 2 m error	Percentage in 3 m error	Average error (m)
KNN	16.67	75.00	2.7011
Kalman	38.89	88.89	2.2400
Proposed algorithm	66.67	88.90	1.9476

Input: fingerprint $(x, y, RSS_1, RSS_i, \ldots, RSS_m)$ of anchor location in indoor environment and the signals measured by target node $(S_1, S_2, \ldots, S_m)$.
Output: the target node's location curve resulting from the operation of the algorithm.
(1) (x, y) = KNN % Using the KNN algorithm to find k nearest position and get the observation values;
(2) $(X, Y) = \left(\sum_{i=1}^{N} \omega_k^i x_k^i, \sum_{i=1}^{N} \omega_k^i y_k^i\right)$ % Input the observation values (x, y) to the particle filter algorithm.
(3) The filtering condition is as follows:

$$P_t < P_{t-1} + T * v_{\max} \text{ \% The distance between two adjacent locations should be smaller than } T * v_{\max}$$

$$\begin{cases} S \notin \{U - \{a, b\}\} \text{ \% When the target is covered by two anchors} \\ S \notin \{U - a\} \text{ \% When the target is covered by one anchor} \\ S \notin U \text{ \% When the target isn't covered by any anchor} \end{cases}$$

$$P_t = \begin{matrix} P_{t1}, (P_{t-1} + T * v_{\max} < P_{t2}) \\ P_{t2}, (P_{t-1} + T * v_{\max} > P_{t2}) \end{matrix}$$

% The topology constraints.

(4) Until all times' positioning and tracking is over, one can get the final positioning tracking curve.

Algorithm 1: Indoor pedestrian tracking.

4. Simulation Evaluation

To verify the effectiveness of the algorithm above, we simulated the algorithm using MATLAB platform by simulating an indoor corner in the building of the computer school of China University of Mining and Technology. We compare the proposed algorithm that combines the particle filter and topology constraints with the other indoor localization algorithms. The simulated environment and the AP distribution are shown in Figure 3.

Because the anchor node deployment is not dense, the changes of the complexity environment often cause indoor pedestrians' nodes positioning not always receiving more than three anchor node's signals. As shown in Figure 3, there is a dotted line which only receives two anchor node's signals, which will cause the intermittent failure positioning problem.

In order to evaluate the performance of the proposed algorithm, the algorithm was compared with the traditional KNN algorithm and Kalman filter algorithm. Experimental model parameters are specified as follows: the maximum rate of mobile target node $v_{\max}$ is 1.3 m/s and the targets locate themselves every T ($T = 1$ s) time. In the KNN algorithm, the parameter k is set to 4. The number of particles N is set to 200 in particle filter algorithm. To ensure the reliability of the experimental results, this study samples 36 times and locates and tracks 50 times repeatedly to get the average data. The location errors are shown in Figure 4. We can observe that the tracking performance of our algorithm is better than the KNN algorithm and the Kalman filter algorithm, although the distribution of errors is difficult to figure out in the figure. In Figure 5, we draw the percentage error of the cumulative distribution every 0.5 m error interval. It can be seen that the algorithm error percentage is 2 m and 3 m, so the proposed algorithm in this paper has a better advantage.

The statistical results of the test data are shown in Table 1. It can be seen that the proposed particle filter and the indoor topology constraints algorithm can obtain better tracking precision. The average error of KNN and Kalman filter algorithm is 2.7011 meters and 2.24 meters, respectively, while the error of the proposed algorithm is 1.9476 meters. Compared with the KNN and Kalman filter algorithm, the percentage of the error that is smaller than 2 meters is increased to 66.67%. And, the percentage of the error that is smaller than 3 meters is increased to 88.91%. The simulations show that when combined with indoor topology constraints, positioning effect can be improved efficiently.

5. Conclusion

Indoor localization is the research hotspot in location based on services. At present, most of the indoor positioning research focuses on anchor nodes deployed sufficiently without considering the change of indoor environment. This may lead to weaker signal that cannot be used to locate. Or anchor nodes' fault can cause the sparse deployment, which leads to intermittent positioning failure problem. To this end, we put forward an indoor positioning algorithm under sparse anchor nodes by building an indoor radio-frequency fingerprint map and using KNN algorithm to obtain initial position location under the condition of sufficient anchor nodes, while one gets optimal positioning location with

sparse anchor node by a series of constraints measures and uses particle filter tracking algorithm to solve nonlinear state space problems. Simulation experiments show that our algorithm can achieve good positioning and tracking results.

The indoor target tracking is a huge and complex engineering, and many issues still remain to be explored. Our ongoing work is as follows: (1) because the anchor placement has direct influence on the tracking accuracy, we will further study the indoor placement problem of anchors; (2) in the indoor environment, there may be multiple targets; thus, we will extend the proposed algorithm for multiple targets tracking; and (3) in the future, we shall consider the detailed hardware implementation and extend this work into the real scenario.

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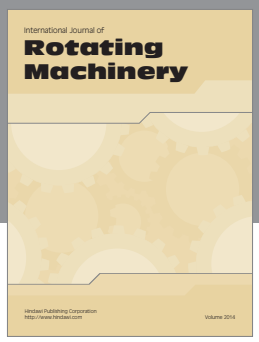

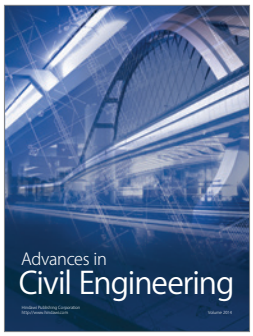

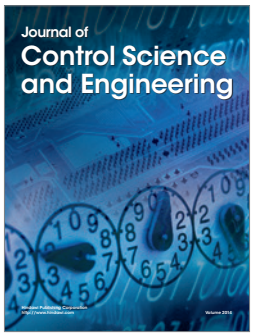

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