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The control of an upper extremity exoskeleton for stroke rehabilitation: An active force control scheme approach

Anwar P.P. Abdul Majeed*, Zahari Taha, Muhammad Amirul Abdullah, Kamil Zakwan Mohd Azmi and Muhammad Aizzat Zakaria

Innovative Manufacturing, Mechatronics and Sports Laboratory, Faculty of Manufacturing Engineering, Universiti Malaysia Pahang. 26600 Pekan, Pahang, Malaysia

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Abstract. This study evaluates the efficacy of a class robust control scheme namely active force control in performing a joint based trajectory tracking of an upper limb exoskeleton in rehabilitating the elbow joint. The plant of the exoskeleton system is obtained via system identification method whilst the PD gains were tuned heuristically. The estimated inertial parameter that enables the AFC disturbance rejection effect is attained by means of a non-nature based metaheuristic optimisation technique known as simulated Kalman filter (SKF). It was demonstrated from the present investigation that the proposed PDAFC scheme outperformed the classical PD algorithm in tracking the prescribed trajectory both in the presence and without the presence of disturbance attributed by the mannequin limb weights (1 kg and 1.5 kg) that mimics the weight of actual human limb weight. Therefore, it is apparent from the results obtained from the present study that the proposed control scheme, i.e., PDAFC is suitable for the application of exoskeleton for stroke rehabilitation.

Keywords: rehabilitation; upper limb exosckeleton; active force control; simulated kalman filter

1. Introduction

Approximately 21,000 stroke cases are reported each year in Malaysia, causing 2,000 deaths and 19,000 significant disabilities (Nazifah *et al.* 2012). The survivors would consequently require assistance with their activities of daily living (ADL). A considerable amount of literature has suggested that continuous and repetitive rehabilitation activities allow them to relearn and regain their complete or partial loss of motor control (Abdul Majeed *et al.* 2017, Loureiro *et al.* 2011, Volpe *et al.* 2002). However, conventional rehabilitation therapy is believed to be costly and labour demanding, hence limiting the patients' rehabilitation activities (Volpe *et al.*, 2002). The adoption of robotics, conversely, has the ability to mitigate the drawbacks of conventional rehabilitation therapy(Lo and Xie 2012, Loureiro *et al.* 2011, Volpe *et al.* 2002). The utilisation of exoskeletons may progressively phase out the long hours taken for rehabilitation and consultation sessions, subsequently permitting the therapist to cater a larger pool of patients (Majeed *et al.*

*Corresponding author, Senior Lecturer, E-mail: amajeed@ump.edu.my

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2017).

Joint-based trajectory tracking control is of particular importance, specifically in the early stage of rehabilitation whereby passive mode is non-trivial in order to improve the patient's mobility via continuous and repetitive exercise on the affected limb. A proportional-derivative (PD) controller was used to control an upper limb exoskeleton that rehabilitates the scapula joint (Carignan *et al.*,. Kawasaki *et al.* (Kawasaki *et al.* 2007) also utilised the PD control strategy in the control of eighteen degrees of freedom (DOF) hand exoskeleton that supports the thumb and fingers motions. However, it is worth noting that although the performance of PD based controllers is satisfactory for trajectory tracking, it does not perform well in the event that disturbances are introduced.

Rahman *et al.* (2010) employed applied a nonlinear sliding mode control (SMC) strategy on a two DOF exoskeleton robot (ExoRob) that tracks the trajectory of the elbow and forearm. They further employed the technique on a 5 DOF exoskeleton dubbed as motion assistive robotic exoskeleton for superior extremity, MARSE-5 (Mohammad Habibur Rahman *et al.* 2012). It is intended to perform trajectory tracking of the shoulder, elbow and forearm movements. Nonetheless, the underlying problem that is often associated with SMC is the chattering phenomenon that may excite the unmodeled high-frequency dynamics, which in turn may degrade the performance of the system (Pi and Wang 2011).

A non-linear modified computed-torque control scheme was also utilised on the ExoRob to perform a number of trajectory tracking that is typically used for passive rehabilitation exercise of the elbow as well as the forearm (Mohammad Habibur Rahman *et al.* 2011). Nonetheless, it is a well-known fact that such ‘model-based’ controllers highly depend on the exact modelling of the system to achieve ‘ideal’ performance, albeit additional controllers may be included to compensate for modelling errors (Craig 2005).

Intelligent based controllers have also been utilised in rehabilitation robotics. Xu *et al.* (Xu *et al.* proposed a fuzzy-based PD position control strategy on a Whole-Arm Manipulator (WAM) for a number of predefined trajectories in order to execute passive recovery training of the impaired limb. It was found that the control architecture is able to move along the predefined trajectories even in the event that disturbances were introduced. However, it is worth to note that the inherent limitations of fuzzy controllers, namely the formulation of the fuzzy rules as well as its extensive inference testing.

Active Force Control (AFC) has been demonstrated both numerically as well experimentally to be robust in disturbance rejection on different applications (Hashemi-Dehkordi *et al.* 2014, Ismail and Varatharajoo 2016, Kwek *et al.* 2003, Mailah *et al.* 2009, Noshadi *et al.* 2012, Zahari Taha *et al.* 2017, Tahmasebi *et al.* 2013a, Tavakolpour Saleh *et al.* 2012, Varatharajoo *et al.* 2011). It is worth noting that such desirable trait is an essential requirement for an exoskeleton that has to accommodate different patients’ anthropometric parameters, in particular, the weight of the affected limb. A hybrid proportional-derivative (PD) simulated Kalman filter (SKF) optimised active force control is investigated with respect to its ability to perform joint tracking objectives as well as its robustness in disturbance rejection of a single degree of freedom upper limb exoskeleton system that is aimed at rehabilitating the flexion and extension of the elbow joint.

2. Control architecture

The notion of AFC was initially conceived by Hewit and Burdess (1981) in the early eighties established on the principle of invariance and Newton’s second law of motion. The efficacy of this method relies on the appropriate approximation of the inertial parameters of the dynamic system.

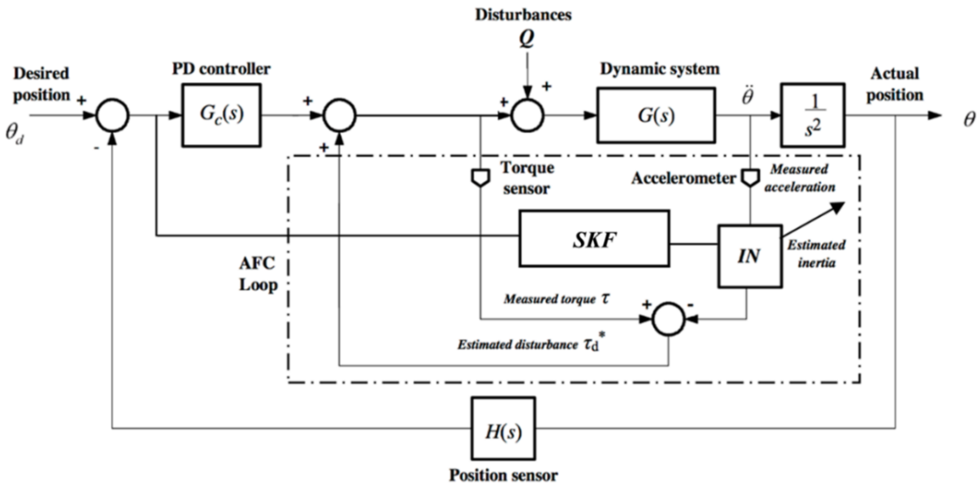


Fig. 1 The PD with SKF based AFC scheme for the control of the upper limb exoskeleton

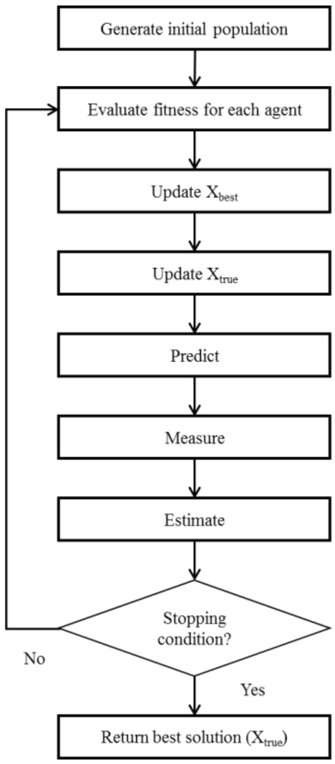


Fig. 2 The SKF algorithm

Different types of intelligent methods have been applied by researchers in estimating the inertial matrix of the dynamic system, i.e., iterative learning (Kwek *et al.* 2003, Musa Mailah *et al.* 2012), neural networks (Tahmasebi *et al.* 2012, 2013b), genetic algorithm (Musa Mailah *et al.* 2002), fuzzy logic (Jahanabadi *et al.* 2011) and particle swarm optimisation (Abdul Majeed *et al.* 2017, Zahari Taha *et al.* 2017) amongst others. A graphical representation of the SKF based AFC scheme with the PD controller applied to the exoskeleton system is illustrated in Fig. 1. The PDAFC control scheme is engaged upon the activation of the AFC loop, without its initiation the system is regulated by the classical pure PD architecture.

In the present study, SKF is utilised to acquire the estimated inertial value of the exoskeleton system. SKF is a relatively new non-nature based metaheuristic optimisation algorithm developed by Ibrahim *et al.* (2015) based on the estimation capability of the Kalman filter. The individual agents in SKF are considered to be individual Kalman filter and based on the mechanism of Kalman filtering, i.e., prediction, measurement and estimation, the global maximum or minimum may be estimated based on an objective function (Muhammad *et al.* 2015). The actual measurement process that is required in Kalman filtering is mathematically modelled and simulated instead. The agents then communicate amongst themselves to update and improve the solution during the search process.

Consider n number of agents, the algorithm begins its initialisation by randomly position each state of the agents $\mathbf{X}(0)$ within the search space as well as the maximum number of iteration, t_{max}. The initial value of the error covariance estimate, $P(0)$, the process noise, Q and the measurement noise, R are also defined during the initialisation stage. The individual agents are then subjected to the fitness evaluation to produce initial solutions $\{\mathbf{X}_1(0), \mathbf{X}_2(0), \mathbf{X}_3(0),\ldots, \mathbf{X}_{n-2}(0), \mathbf{X}_{n-1}(0), \mathbf{X}_n(0)\}$. The fitness values are compared and the agent that possess the best fitness value at each iteration, t is registered as $\mathbf{X}_{best}(t)$. The best solution so-far is denoted as $\mathbf{X}_{true}(t)$ and it is only updated if a better solution is found.

The ensuing calculations mimic the predict-measure-estimate mechanism of the Kalman filter. The following time update equations known as the *a priori* estimates are employed in the prediction step.

$$\mathbf{X}(t|t-1) = \mathbf{X}(t-1) \tag{1}$$

$$P(t|t-1) = P(t-1) + Q \tag{2}$$

where $\mathbf{X}(t-1)$ and $\mathbf{X}(t|t-1)$ are the previous state and the predicted/transition state, respectively. Conversely, $P(t-1)$ and $P(t|t-1)$ are the previous and transition error covariant estimate. It is worth to note that the error covariant estimate is influenced by the process noise, Q. This if followed by the measurement step, which is essentially a feedback to the estimation process. The measurement is modelled in such a manner that its output may take any value from the predicted state estimate, $\mathbf{X}(t|t-1)$, to the true value, $\mathbf{X}_{true}$. The measurement, $\mathbf{Z}_i(t)$ of each individual agent, is simulated by the following governing equation

$$\mathbf{Z}_i(t) = \mathbf{X}_i(t|t-1) + \sin(rand\ \times\ 2\pi) \times \left|\mathbf{X}_i(t|t-1) - \mathbf{X}_{true}\right| \tag{3}$$

The $\sin(rand \times 2\pi)$ term provides the stochastic aspect of the SKF algorithm. The final step is the estimation where the Kalman gain, $K(t)$ is computed. The gain may be computed as follows

$$K(t) = \frac{P(t|t-1)}{P(t|t-1) + R} \tag{4}$$

Then the following *a posteriori* estimates are computed based on Eqn. (9), where the error covariant is updated based on Eq. (10) to provide the optimum position for that corresponding iteration. The subsequent iteration is executed until the maximum number of iteration, t_{max} is reached. Fig. 2 depicts the flowchart of the SKF algorithm.

$$\mathbf{X}_i(t) = \mathbf{X}_i(t|t-1) + K(t) \times \left(\mathbf{Z}_i(t) - \mathbf{X}_i(t|t-1)\right) \tag{5}$$

$$P(t) = \left(1 - K(t)\right) \times P(t|t-1) \tag{6}$$

3. Results and discussion

The plant of the exoskeleton system shown in Fig. 3 was obtained via system identification. The details on the attainment of the plant are deliberated in (Taha *et al.* 2017). The plant identified is as follows

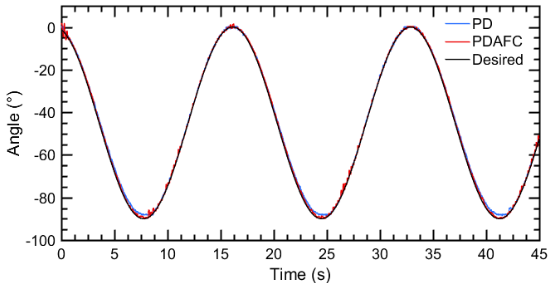
$$G(s) = \frac{386.5}{s^3 + 14.06s^2 + 65.01s + 9.182} \tag{7}$$

Furthermore, the PD parameters were tuned appropriately to achieve reasonable trajectory tracking. The PD gains are heuristically tuned from the identified model are 53.4771 and 0.71227 for K_p and K_d, respectively. The **IN** for the AFC loop was obtained via the minimisation of the root

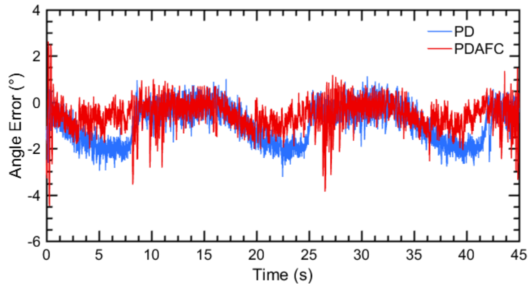
Fig. 3 The upper limb exoskeleton system

Table 1 Trajectory tracking performance

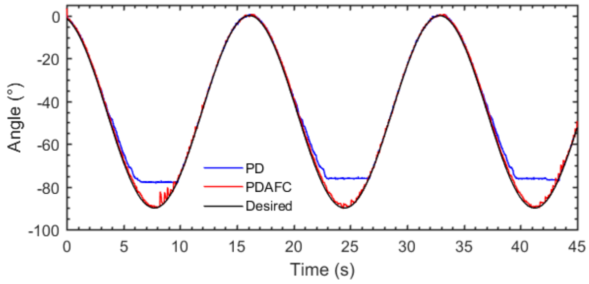
Error Metrics (°)	No Disturbance		Disturbance, 1.0 kg		Disturbance, 1.5 kg	
	PD	PDAFC	PD	PDAFC	PD	PDAFC
ME	0.9625	0.5753	3.4430	0.8126	6.9533	1.1149
RMSE	1.2398	0.8492	5.4457	1.1262	11.0446	1.4856
MAE	0.9989	0.6622	3.4805	0.8542	6.9633	1.1660



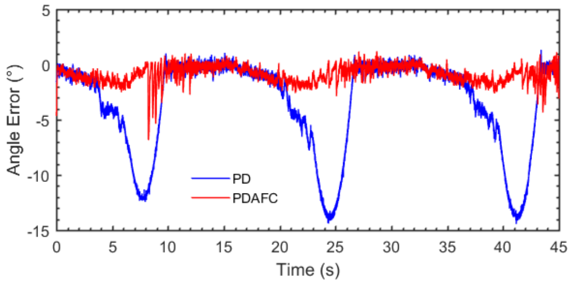
(a) Elbow trajectory tracking with no disturbance



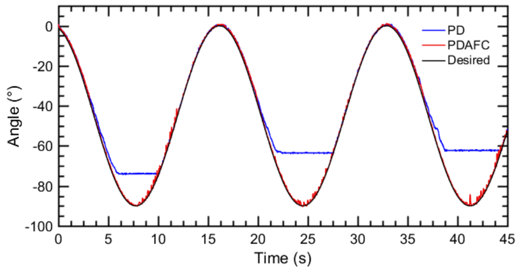
(b) Elbow tracking error with no disturbance



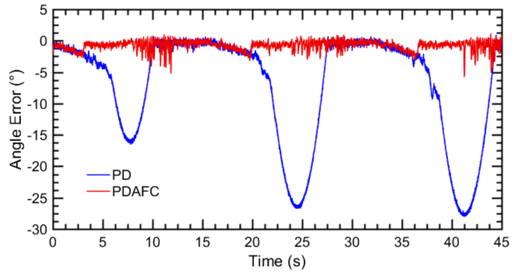
(c) Elbow trajectory tracking with 1.0 kg disturbance



(d) Elbow tracking error with 1.0 kg disturbance



(e) Elbow trajectory tracking with 1.5 kg disturbance



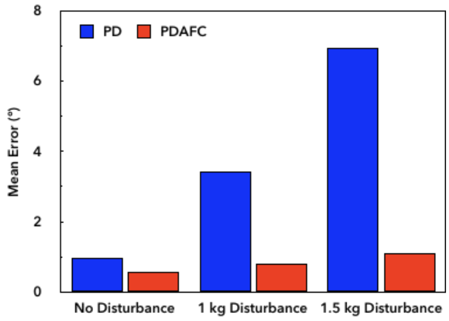
(f) Elbow tracking error with 1.5 kg disturbance

Fig. 4 The trajectory tracking and tracking error of the exoskeleton with and without the influence of mannequin weight as a form of disturbance to the system

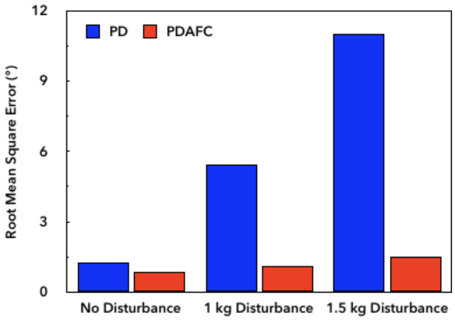
mean square error (RMSE) for a population size of 20 and an iteration of 100. The initial value of the error covariance estimate, $P(0)$, the process noise, Q and the measurement noise, R parameters for the SKF algorithm are taken as 1000, 0.5 and 0.5, respectively (Ibrahim *et al.* 2015). Through the proposed optimisation technique, the appropriate IN value attained is 0.000913289 A.s^2

A sinusoidal signal with an amplitude of 90° and a frequency of 0.375 rad/s for a period of 45 seconds is supplied to the system to mimic a common rehabilitation exercise for the elbow joint (Mohammad Habibur Rahman *et al.* 2012). A forearm mannequin with a mass of 1.0 kg and 1.5 kg were attached to the exoskeleton to investigate the efficacy of the controllers, i.e., PD and PDAFC in performing the desired trajectory in the presence of constant disturbance (the weight of the forearm). Table 1 lists the error metrics, i.e. mean error (ME), RMSE and mean absolute error (MAE) that are used to evaluate the performance of the aforementioned controllers.

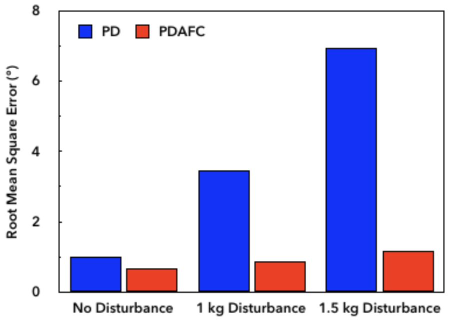
It is evident from the error metrics that the PDAFC scheme is far more superior in comparison to the classical PD control architecture. The effectiveness of the proposed scheme in catering the effect of disturbance, i.e. the weight of the forearm is more pronounced if the weight applied is 1.0



(a) Mean Error



(b) Root mean square error



(c) Mean absolute error

Fig. 5 The tracking performance of the exoskeleton in terms of error metrics

kg and 1.5 kg. Furthermore, it could be seen from Figs. 4((a)-(f)) that the classical PD scheme is unable to track the desired trajectory, nonetheless, the PDAFC scheme is able to mitigate the gravitational effect of the forearm. It is worth to note that the erratic spikes are primarily due to the limitations of the physical structure of the exoskeleton prototype. A similar observation was also made by Jahanabadi *et al.* (2011) concerning this issue. Nevertheless, this shortcoming could not negate the fact on the ability of the proposed control architecture in catering different weights whilst providing reasonably accurate trajectory tracking as demonstrated via the error metrics bar charts in Figs. 5(a)-5(c), respectively.

4. Conclusions

It is evident from the present investigation that the proposed AFC-based control scheme is quite robust in the wake of disturbance arising from the mannequin limb weights that mimics the weight of actual human limb. The simplicity of the proposed control algorithm further for its ease of implementation. Future studies would include the different types of rehabilitation regimes to improve the motor skills of the impaired joint as well as the ability of the proposed controller in accomplishing it.

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