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Data Driven Kinematic Modeling of Human Gait for Synthesize Joint Trajectory

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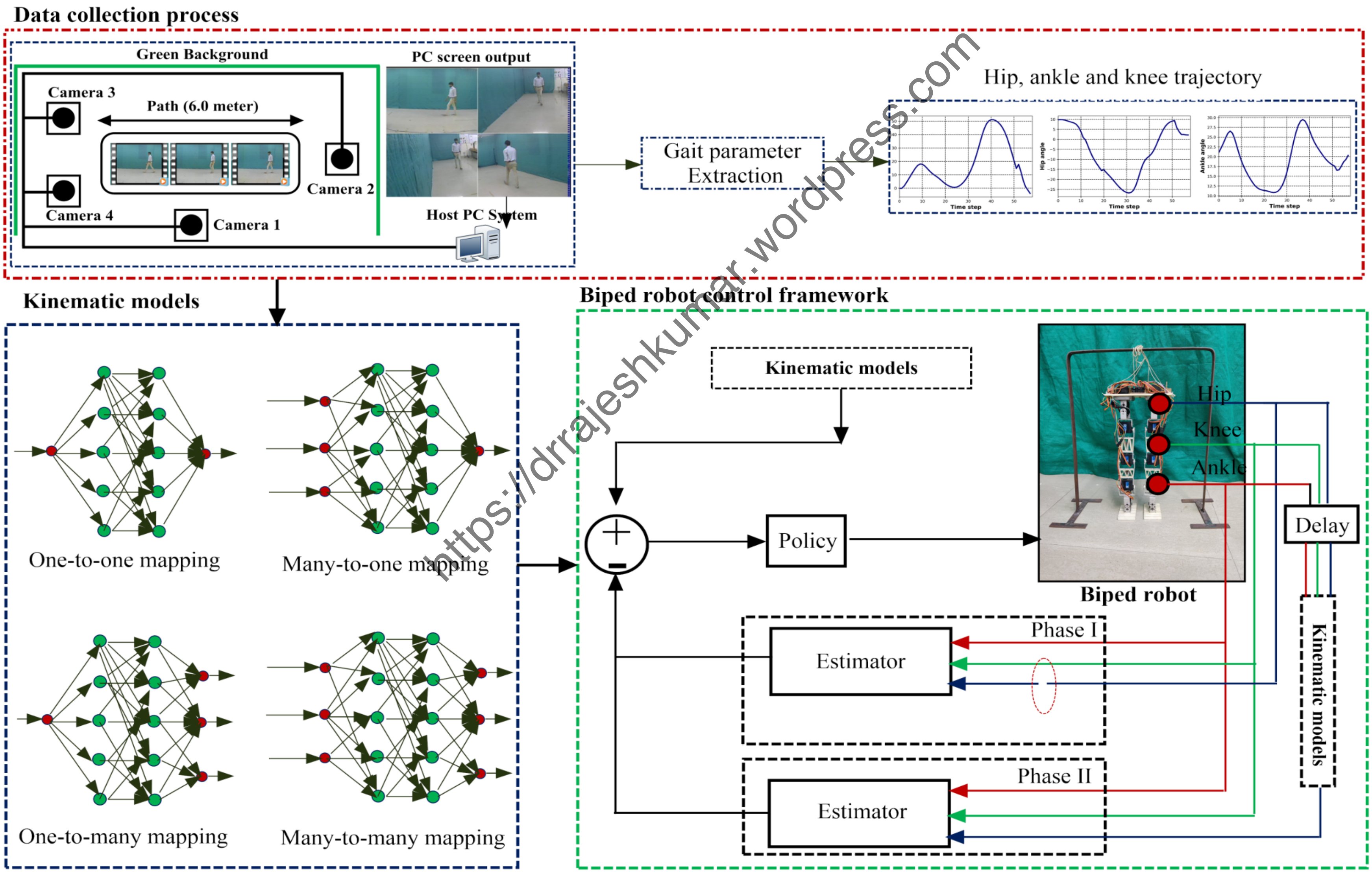
Presentation Outlines

- Introduction
- Methodology
- Deep learning models
- Model parameters
- Results
- Conclusion
- References

Introduction

- Synthesis of reference joint trajectories for the legged robot is a very difficult task due to higher degrees of freedom.
- This work presents the kinematic modeling of human gait data, which is used as the reference joint trajectory for a Biped robot, 8 deep learning models are proposed.
- Gait data-set of 120 subjects are collected at RAMAN Lab, MNIT Jaipur, India using the vision-based methodology. All subjects belong to the 5-60 years age group.
- Four type of novel mappings, one-to-one (knee-to-knee, hip-to-hip, and ankle-to-ankle), many-to-one (knee+hip+ankle-to-knee/hip/ankle), one-to-many (knee/ankle/hip-to-knee+hip+ankle), and many-to-many(knee+hip+ankle-to-knee+hip+ankle), are also developed.
- These mapping provides the reference trajectories to biped robot and relationships between the knee/hip/ankle trajectories is also obtained.
- Performance evaluation of developed models is measured by average error, maximum error and root mean square error.

Methodology



Learning models and Parameters

- Multi-layer Perceptron Regressor
- Deep Neural Network
- RNN
- LSTM
- GRU
- Bidirectional RNN
- Bidirectional LSTM
- Bidirectional GRU

S.No.	Parameter	Value/function
1.	λ	0.3
2.	Activation function	relu
3.	Learning rate	0.2
4.	Optimizer	adam
5.	Loss function	mse
6.	Epochs	60

Results I

Model	P.I.	Knee-to-knee	Hip-to-hip	Ankle-to-ankle
MLP	AE	6.2908	1.9121	5.5197
	ME	23.7771	4.7296	11.2024
	RMSE	9.4732	2.3151	6.36319
DeepNN	AE	2.8857	1.4954	0.7807
	ME	6.5401	3.309	2.1124
	RMSE	1.6987	1.2228	0.8835
RNN	AE	3.0781	1.7569	1.1838
	ME	6.0731	3.6246	1.3255
	RMSE	1.7544	2.8473	1.0881
LSTM	AE	3.1862	1.6079	**0.9155**
	ME	6.2777	3.4711	**2.4823**
	RMSE	1.7851	1.2681	**0.9568**
GRU	AE	2.6207	1.5868	1.4354
	ME	7.7649	5.5331	3.0667
	RMSE	1.6188	1.2596	1.1981
Bi-RNN	AE	2.6454	1.4872	1.0455
	ME	6.3375	4.4308	2.8836
	RMSE	1.6264	1.2195	1.0224
Bi-LSTM	AE	2.6951	1.7883	1.117
	ME	7.3271	4.3861	2.8323
	RMSE	1.6416	1.3372	1.0543
Bi-GRU	AE	**2.5379**	**1.3471**	1.2121
	ME	**6.3704**	**3.93727**	2.2754
	RMSE	**1.5931**	**1.1606**	1.1009

- It allows the comparative analysis of developed deep learning models for the one-to-one mapping.

- It shows that bidirectional GRU outperforms the other models for knee-to-knee and hip-to-hip mapping.

- whereas the LSTM performs best for the ankle-to-ankle mapping.

Results II

Model	P.I.	All-to-knee	All-to-hip	All-to-ankle
MLP	AE	0.7508	**0.2908**	0.4255
	ME	2.1772	**1.0202**	0.9461
	RMSE	1.0395	**0.4409**	0.4999
DeepNN	AE	1.2021	0.4227	0.4001
	ME	6.7663	1.4643	2.4318
	RMSE	1.0963	0.6501	0.6325
RNN	AE	0.9465	0.4091	0.5324
	ME	5.7527	0.8457	3.7236
	RMSE	0.9272	0.63962	0.7296
LSTM	AE	0.9717	0.6979	0.2851
	ME	7.4635	2.4919	1.6657
	RMSE	0.9857	0.8354	0.5339
GRU	AE	0.5615	0.4323	**0.1594**
	ME	5.9958	1.3107	**0.7497**
	RMSE	0.7493	0.6575	**0.3993**
Bi-RNN	AE	1.5585	0.4636	0.7678
	ME	4.6074	1.4691	3.3267
	RMSE	1.2484	0.6808	0.8762
Bi-LSTM	AE	**0.3751**	0.5196	0.3314
	ME	**2.4749**	2.8441	1.9941
	RMSE	**0.6124**	0.7208	0.5757
Bi-GRU	AE	0.4399	0.4585	0.3701
	ME	5.1721	2.1386	3.3212
	RMSE	0.6633	0.6771	0.6083

- ➢It allowed the comparative analysis of developed deep learning models for the many-to-one mapping.
- ➢The result shows that the different models perform differently for different mapping i.e., bidirectional LSTM, MLP, and GRU outperform the other models for all to- knee, all-to-hip, and all-to-ankle respectively.

Results III

Model	P.I.	Knee			Hip			Ankle		
		Knee	Hip	Ankle	Knee	Hip	Ankle	Knee	Hip	Ankle
MLP	AE	6.2908	6.1882	5.5959	2.8889	1.9121	1.5112	5.7116	6.8072	5.5197
	ME	23.7770	23.0906	21.5186	**4.6177**	4.7296	3.2119	10.0522	11.0470	11.2024
	RMSE	9.4732	9.5314	8.7497	3.1759	2.3151	1.7457	6.3620	7.3793	6.3631
DeepNN	AE	2.2318	0.7957	0.7490	1.8833	1.4477	0.4814	2.0431	1.1003	0.9844
	ME	6.6221	2.8798	3.1660	5.3841	4.1839	1.4275	6.4817	6.4971	2.7319
	RMSE	2.8898	1.0266	1.0509	2.3418	1.8002	0.6040	2.5954	1.5826	1.2126
RNN	AE	2.5153	0.7564	0.7222	1.7681	**1.2951**	**0.4414**	1.9912	1.0725	1.0095
	ME	6.9760	2.9882	3.4405	6.8647	**3.6108**	1.7430	6.4393	6.5047	2.7440
	RMSE	3.1482	0.9920	0.9958	2.3420	**1.5882**	**0.5680**	2.5317	1.5642	1.1940
LSTM	AE	2.2272	0.6867	0.7336	1.9510	1.4344	0.4589	1.9830	1.1009	0.9903
	ME	6.7782	2.4175	3.1123	6.2262	5.3095	1.4122	6.8111	**5.9199**	2.8252
	RMSE	3.0288	0.9174	1.0359	2.4693	1.8006	0.5887	2.5359	1.4522	1.1827
GRU	AE	**2.1811**	**0.6785**	0.7299	1.8018	1.4670	0.5372	2.1175	1.1184	1.0252
	ME	7.0002	2.9725	3.1526	5.3978	4.1449	**1.3949**	6.9679	6.4279	2.6979
	RMSE	**2.8436**	**0.8854**	0.9578	2.2431	1.7888	0.6902	2.6519	1.5766	1.2132
Bi-RNN	AE	2.5162	0.9740	0.8737	**1.7411**	1.5281	0.5239	1.9245	1.1308	0.9969
	ME	6.5980	7.5067	**2.7951**	6.9135	4.2636	1.9123	**6.4265**	6.6706	2.6770
	RMSE	3.1485	1.5105	1.0821	**2.3221**	1.7872	0.6627	2.4277	1.5561	1.1570
Bi-LSTM	AE	2.4909	0.6930	0.8238	1.7672	1.5071	0.5268	**1.7629**	**0.9758**	**0.9723**
	ME	**6.4556**	**2.3855**	3.1655	7.2391	5.3377	2.2171	6.7405	6.1717	**2.6433**
	RMSE	3.1430	0.9113	1.0409	2.3997	1.8676	0.6965	**2.3408**	**1.3531**	**1.1689**
Bi-GRU	AE	2.3665	0.6941	**0.6686**	1.8536	1.5886	0.4701	2.0579	1.2249	1.0280
	ME	6.5966	2.8493	3.4161	5.9284	5.1301	1.4402	6.7122	7.1923	2.7927
	RMSE	3.0855	0.8918	**0.9323**	2.4509	1.9616	0.5602	2.5798	1.6024	1.2092

- It allows the comparative analysis of developed deep learning models for the one-to-many mapping.
- The result shows that the different models perform differently for different mapping.
- **Knee-to-all mapping:** GRU and bidirectional GRU out-performs the knee to knee/hip and knee to ankle mapping based on the average/root mean square error respectively. Whereas, bidirectional LSTM is performing well based on the maximum error indices.
- **Hip-to-all mapping:** RNN outperforms the other models.
- **Ankle-to-all mapping:** bidirectional LSTM has outperformed the other models based on the performance indices.

Results IV

Model	P.I.	All		
		Knee	Hip	Ankle
MLP	AE	0.7508	0.4255	0.2908
	ME	2.1772	0.9461	1.0202
	RMSE	1.0395	0.4999	0.4409
DeepNN	AE	0.1240	0.0593	0.0493
	ME	1.0038	0.3087	0.1952
	RMSE	0.2127	0.0846	0.0675
RNN	AE	0.1469	0.0491	0.0253
	ME	0.7479	0.3023	0.1014
	RMSE	0.2213	0.0753	0.0339
LSTM	AE	0.1035	0.0536	0.0585
	ME	0.7986	0.2035	0.1882
	RMSE	0.1742	0.0689	0.0724
GRU	AE	0.07135	0.0544	0.0431
	ME	0.7855	0.1421	0.1559
	RMSE	0.1585	0.0644	0.0602
Bi-RNN	AE	2.4752	1.3835	0.9294
	ME	6.4118	3.9395	2.8009
	RMSE	3.1036	1.7338	1.1592
Bi-LSTM	AE	**0.04581**	**0.0298**	**0.0234**
	ME	0.9549	**0.1144**	**0.1227**
	RMSE	0.1203	**0.0391**	**0.0327**
Bi-GRU	AE	0.0827	0.0643	0.0331
	ME	**0.5594**	0.1854	0.2575
	RMSE	**0.1171**	0.0757	0.0443

- It allowed the comparative analysis of developed deep learning models for the many-to-many mapping.

- The result shows that the bidirectional LSTM outperforms the other models for the all-to-hip/ankle whereas bidirectional GRU performs best for the all-to-knee mapping.

- Overall, bidirectional deep learning methods outperform all other approaches, and also many-to-many mapping outperforms all other mappings.

Conclusion and Future Scope

- This presented the kinematic modeling of the gait data-set of humans using deep learning approaches (multi-layer perceptron, deep neural network, recurrent neural network, long-short term memory, gatted recurrent unit, and their bidirectional networks).

- The result shows that the bidirectional deep learning approaches outperform all other methods. In addition, the many-to-many mapping performs better than all other mappings.

- Overall, this study is helpful in multiple ways, (a) reference gait trajectory generation, (b) next time step state estimation in case of some onboard sensor failed, (c) one sensor can be useful to estimate the next joint position, and (d) next time control can be evaluated in advance.

- Certain issues can be tackled in the future like data-processing and tuning of hyper-parameters of models using the global optimizer.

- As a future scope, the authors will implement the above-proposed mapping models on the real biped robot.

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THANK YOU